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RISING CONCERN ON FOOD SECURITY: FROM A GLOBAL PERSPECTIVE

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DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the FYP.

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LIST OF ABBREVIATIONS

AIFSCF	Alaskan Inuit Food Security Conceptual Framework
BPLM	Breusch-Pagan Lagrangian Multiplier
COVID-19	Coronavirus Disease
CSD	Cross-Sectional Dependence
FAO	Food and Agriculture Organization of the United Nations
FAOSTAT	Food and Agriculture Organization Statistics
FEM	Fixed Effects Model
GDP	Gross Domestic Product
IPCC	Intergovernmental Panel on Climate Change
LR	Likelihood Ratio
NAFTA	North America Free Trade Agreement
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
REM	Random Effects Model
SDG	Sustainable Development Goals
US	United States
WDI	World Development Index
WMO	World Meteorological Organization
WTO	World Trade Organization

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PREFACE

Food stability is becoming a more pressing global concern, especially when it comes to food security. The consequences of food insecurity are serious, including malnutrition, hunger, economic instability, and social unrest. As food security is not limited to individual nations but is seen as a global issue, it receives a lot of focus from policymakers, researchers, and international organizations. Insufficient food security can result in serious outcomes such as lower economic output, higher healthcare expenses, and societal tensions.

Climate change, conversely, is a crucial factor in worsening issues with food security. The significant shifts in weather conditions, specifically the increase in land temperatures, greatly influence the productivity of agriculture. The alterations interfere with the development of crops, diminish agricultural yields, and stress water supplies, ultimately impacting the availability and reliability of food. Additionally, opening up trade has been used as a tactic to lessen the negative impacts of climate change and enhance food security. Trade openness seeks to protect against local scarcities and stabilize food availability by enabling the exchange of goods and resources. Nevertheless, the recent changes in trade patterns, influenced by protectionism, political conflicts, and trade wars, have made this strategy more complex and worsen the issue of food insecurity.

This research seeks to explore how trade openness and climate change affect food security, specifically examining how they interact with each other. We aim to assess if opening up trade can effectively address the food security challenges brought about by climate change. The study will analyze climate change, trade openness, and their interaction to understand how they collectively impact food security.

ABSTRACT

Countries around the world are confronted with the challenge of ensuring food security, which has major impacts on global stability and overall health. This research investigates how food security, climate change, and trade openness are interlinked and impact food stability. We examine information from 151 nations over the time frame of 2001 to 2020, with 2,961 observations, utilizing strong panel data methods. In our analysis, we use various methods such as pooled least squares, fixed effects, random effects, and Driscoll-Kraay standard error estimation to guarantee the reliability of our findings. The results show a strong link between trade openness and food stability, suggesting that while trade openness can improve food security, it may also worsen food stability problems in specific circumstances. Furthermore, there is a strong positive correlation between food stability and the interaction of trade openness and climate change, indicating that the impact of these variables together could exacerbate food security. On the flip side, this research suggests that the impact of climate change on food security is not as significant as previously believed, as it has a low relationship with food security. This emphasizes the intricate interactions among these factors and emphasizes the necessity of specific approaches to tackle the various aspects of food security issues.

CHAPTER 1: RESEARCH OVERVIEW

1.1 Research Background

1.1.1 Food Security

Food security, as defined by World Bank Group (2023) is a mean of ensuring a supply of food sufficiently large to meet the dietary needs of people in a particular location, socially and culturally accepted and available to individuals, moreover, enable people to lead a healthy lifestyle. According to Li & Song (2022) and Adem (2021), food security consists of 4 main dimensions which comprises of food availability, economic and physical access to food, use and utilization of food and food stability or maintaining over the time. While all these dimensions are important, a country or region can still be considered food secure if it excels in some dimensions but falls short in others. For example, a region might have high availability and accessibility of food but struggle with utilization due to poor food preparation or storage practices.

Food availability is heavily influenced by climate change, as shifting weather patterns and extreme weather events disrupt agricultural productivity. For instance, prolonged droughts can severely affect crop yields, while excessive rainfall can lead to flooding, damaging harvests and reducing the supply of food. Additionally, market fluctuations can create instability in food availability; sudden increases in commodity prices can make staple foods unaffordable for many households, particularly in low-income regions. Research in Brazil indicated that regional disparities in agricultural production often lead to unequal food distribution, resulting in some areas experiencing food surpluses while others face shortages (Lima et al., 2020). Furthermore, global supply chain disruptions, as seen during the COVID-19 pandemic, highlighted vulnerabilities in food availability, where lockdowns and transportation restrictions hindered food distribution, exacerbating food insecurity in many communities.

Besides, accessibility of food, encompassing affordability, transportation, and distribution networks, presents significant challenges that hinder food security for many populations. In rural Ethiopia, for example, research has shown that while some households may achieve food security during certain periods, they remain vulnerable to transitory or chronic food insecurity due to their limited access to food markets and resources. This situation is exacerbated by poor infrastructure, which hampers transportation and increases the cost of food delivery, making it difficult for remote communities to obtain essential supplies. Similarly, a study on regional disparities in food security in Spain found that certain areas experienced heightened levels of food insecurity due to restricted access to protein-rich foods, highlighting how geographic and economic factors can create uneven food distribution and accessibility (Ashby et al., 2016). Furthermore, the alarming statistic that 870 million people, or 12.5% of the global population, face starvation primarily in developing countries underscores the pressing need to address issues of affordability and access to nutritious food (Smith et al., 2000).

Furthermore, food security increasingly faces challenges related to food utilization, which encompasses the effective use of food to meet dietary needs and promote health. A significant issue is the uneven distribution of essential nutrients, where certain populations may have access to food but lack the variety needed for a balanced diet. This disparity often results from improper food handling and preparation practices, leading to nutrient loss and increased risk of foodborne illnesses (Khan et al., 2023). Moreover, even when food is available, inadequate knowledge about nutrition can prevent individuals from making healthy dietary choices, contributing to malnutrition and related health issues, particularly among vulnerable populations such as children and the elderly. Additional factors, such as a lack of clean water and poor sanitation, exacerbate these problems, as contaminated water can compromise food safety and quality. Cultural practices, which may prioritize certain foods over others, can also limit the diversity of nutrients consumed (Donkor, 2023). This imbalance between food availability and effective utilization undermines overall food security, particularly in regions where educational resources and infrastructure are insufficient to support proper food handling, preparation, and consumption practices.

Among these alternatives, stability of food usually encounters the most problem to the society. The stability of food security as influenced by economic downturns, natural disasters, and policy changes, is a crucial dimension that encounters challenges. A study on the multidimensional measurement of food security in Israel found that stability was a critical factor in determining overall food security levels. Only 20% of households were food secure all the time, while 67% experienced transitory food insecurity and 13% faced chronic food insecurity (Endeweld & Silber, 2018).

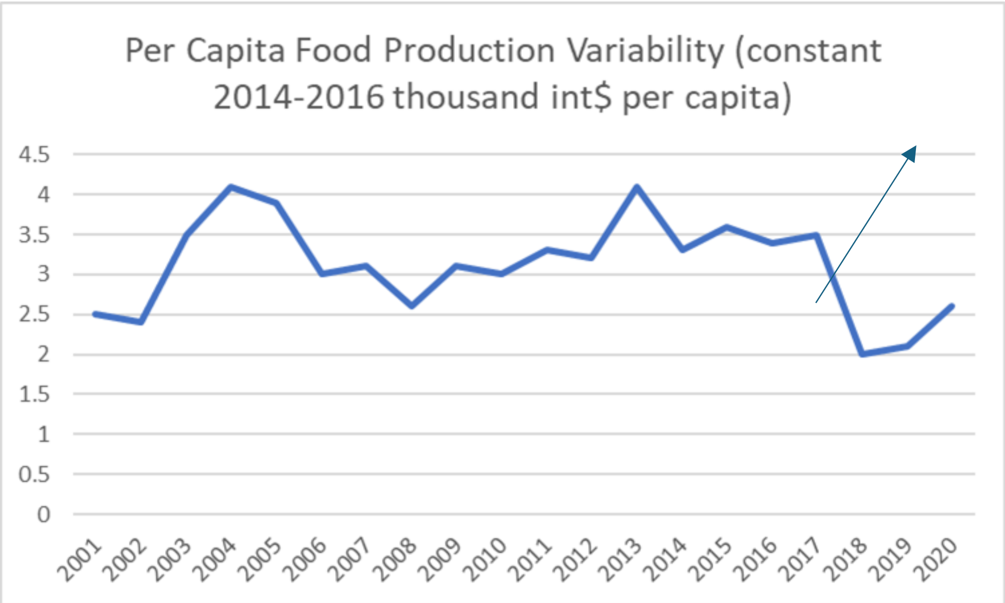
Food stability is seen as more important when it comes to food security, as it guarantees a steady and predictable food production in the long term. Food instability, or the lack of reliable access to sufficient, affordable, and nutritious food, can arise from various factors on the production side of the food system. Modern agriculture has become increasingly dependent on a small number of high-yielding crop varieties. This lack of diversity makes the food system vulnerable to shocks, such as pests, diseases, or extreme weather events that can devastate a single crop variety. When a dominant crop fails, it can lead to severe food shortages and price spikes, contributing to food instability (Verhoueven, 2019). Consistency in food supplies is crucial in preventing fluctuations that may result in shortages or excess, ensuring a steady and reliable access to food. Lack of stability can hinder food security efforts, despite the availability and accessibility of food. Furthermore, consistent food provisions aid in economic strategizing and progress by enabling people and nations to budget, strategize, and allocate resources more efficiently, lessening economic instability from fluctuating food costs (García-Díez et al., 2021).

Furthermore, food stability is crucial not only for economic advantages but also for maintaining public health and social stability (Grantham, 2024). A dependable food source guarantees that individuals regularly have access to healthy food, which is essential for sustaining health and efficiency. Regular disturbances may result in malnourishment or food insecurity, which can have a negative impact on public health. Stable food systems help prevent social unrest and conflicts caused by food shortages or price increases. In general, although food availability, access, and utilization are crucial, food stability combines these aspects by ensuring they stay dependable and consistent, highlighting its significance in comprehensive food security.

Among all indicators, per capita food production variability is a significant metric used to assess the stability of food security. This concept encompasses the fluctuations in the amount of food produced per person within a specific region or country, reflecting both agricultural productivity and the resilience of food systems (Kannan & Anandhi, 2020).

Figure 1.1

Per Capita Food Production Variability



Source: Food and Agriculture Organization (2024)

Figure 1.1 illustrates the per capita food production variability across the globe. Starting in 2018, there has been a noticeable increase in global food production variability, marking a shift from the relatively stable pattern observed between 2001 and 2017. This upward trend suggests growing instability in food production, potentially driven by factors such as climate change, economic disruptions, and political instability. As variability increases, the impact on per capita food availability becomes more pronounced, leading to potential food shortages, price hikes, and increased food insecurity, especially in vulnerable regions. This rise in food production variability could also negatively affect nutrition, particularly in developing countries, where fluctuations in food availability might result in poorer diet quality. The magnified effect starting in 2018 highlights the need for strategies to address these emerging challenges in global food security.

To sum up, regardless of the dimension used to measure food security including availability, accessibility, utilization, or stability, it is evident that food security is facing significant challenges and is degrading overall. Stability often encounters the most pressing issues, influenced by economic downturns, natural disasters, and policy changes, which can lead to varying degrees of food insecurity. Food availability is increasingly threatened by climate change, market fluctuations, and global supply chain disruptions, resulting in disparities in food distribution and access. Accessibility, encompassing affordability and transportation, remains a challenge, particularly in rural areas where poor infrastructure limits food market access. Additionally, food utilization suffers from improper handling, inadequate nutritional knowledge, and the uneven distribution of essential nutrients, which can exacerbate malnutrition, especially among vulnerable populations. Collectively, these factors point to a troubling trend in global food security, underscoring the urgent need for comprehensive strategies to address the underlying drivers of food insecurity.

1.1.2 Climate Change

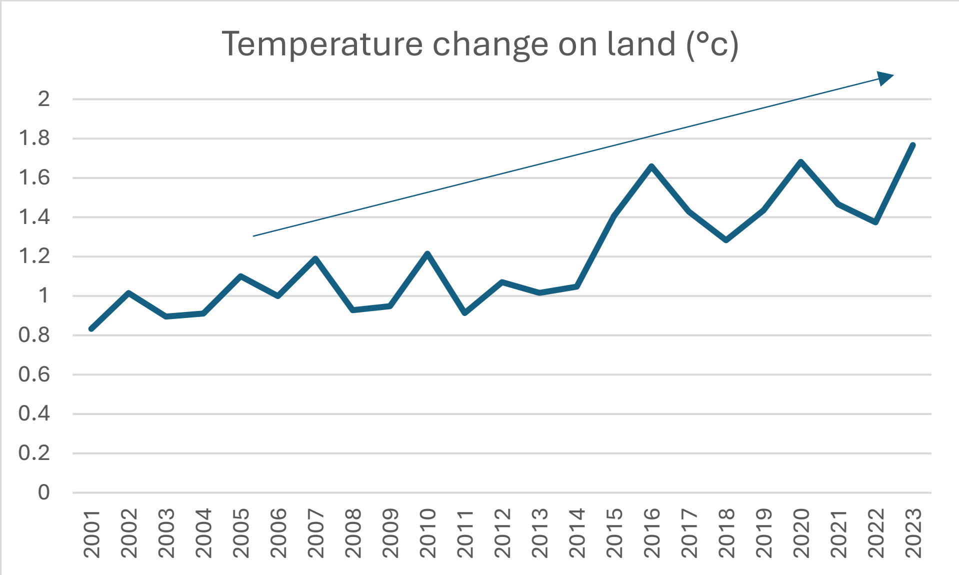
Climate change has been a global phenomenon since the late 20th century, impacting many aspects of our life in different parts of the world. Food security is one of the major aspects that is directly impacted by climate change, as agricultural production is faced with severe challenges and fluctuations in temperature, rain precipitation, extreme weather events etc. as a result of the worsening of climate change, which directly affect global food security. According to the latest report published by the Intergovernmental Panel on Climate Change (2023), the frequency of extreme weather such as heatwaves, floods, droughts etc. has significantly increased, which increased the risks faced by the agricultural sectors, particularly in vulnerable regions such as underdeveloped countries or regions.

The Food and Agriculture Organization of the United Nations (2016) also highlights that climate change has disrupted the global food supply system through a drop in crop yields, changes in pest and disease distribution, and decreased water availability for crop irrigation. These disruptions will reduce food availability as production drops, directly threatening global food security. One of the recent incidents took place in 2022 when drought caused severe food shortages in the Horn of Africa as a result of crop failure and death of livestock, which led to millions of people facing hunger problems (World Food Programme, 2024).

Food security is closely linked to climate resilience, as climate change gets worse, countries will face more difficulty to be able to feed their population. The World Food Programme (2024) identifies those low-income nations, which usually are those who are in the most vulnerable regions with high reliance on agriculture face the most severe effects brought by climate change. This is especially for the case of sub-Saharan Africa and South Asia. These regions already have ongoing food insecurity problems, and climate change will put extra stress on the condition which could make the situation even worse.

Figure 1.2

Temperature Change on Land



Source: World Development Index (2024)

Global temperature change on land has seen a drastic change over the years, especially since the beginning of the 21st century. According to the statistics released by the Food and Agriculture Organization of the United Nations, global temperature change on land has risen from 0.833°c to 1.767°c in 2023, the highest record ever. In a press release in January 2024, the World Meteorological Organization (WMO) announced that 2023 would be the warmest year ever recorded, with the annual global temperature nearing the limit set in the Paris Agreement of not exceeding 1.5° Celsius above pre-industrial levels (World Meteorological Organization, 2024). It is undoubtedly that the drastic increase in global temperature becomes one of the most serious problems food producers faces. Hence, it is really crucial for researchers to study the impact of climate change towards global food security problems as climate change has a very great influence on food security through impacting the global food production.

Although most climate change's effects on food security are negative, some regions might experience short-term benefits, particularly in countries with temperate climate. Past studies have shown that when comparing the impact of climate change between tropical countries, which are located near to the equator) and temperate countries, which are usually located at higher latitudes, temperate countries will have a lower impact on food security than tropical countries (Lobell & Burke, 2009). Some studies have shown that although generally, climate change will affect food production with an increasing temperature, it might benefit temperate climate countries as they will expect warmer weather, which provides a potential for them to yield higher crop production (Mirzabaev et al., 2023). However, these benefits are expected to be outweighed by the long-term negative impacts on the global crop yield with more extreme weather, and eventually impacting the global food security.

Moreover, rise in global temperature is expected to change agricultural zones, with the changes in agricultural practices and crop types due to changing climate, which might affect yields of staple crops such as wheat and maize to be reduced due to temperature fluctuations (Lobell et al., 2011). This will have a great impact on regions that rely heavily on these crops as their main source of food. Therefore, policy researchers need to prioritize and emphasize how climate change contribute into the equation when looking into global food security issue.

1.1.3 Trade Openness

To tackle the issue of food insecurity, trade is frequently recommended as a remedy. Nevertheless, certain nations might be reluctant to engage in trade agreements due to various factors. The main goal of this research is to investigate if trade can mitigate the effects of climate change on food security. In doing this, it aims to determine if trade can still be an effective strategy for enhancing food access and resilience in disadvantaged areas. Trade plays a crucial role in shaping food security, especially for low-income, food-insecure countries that greatly rely on imports to meet their food needs. These countries face financial limitations that restrict their ability to achieve food security through imports, as they depend not only on food imports but also on other essential commodities like fertilizers, fuels, and medicine (Morgan & Sagener, 2016).

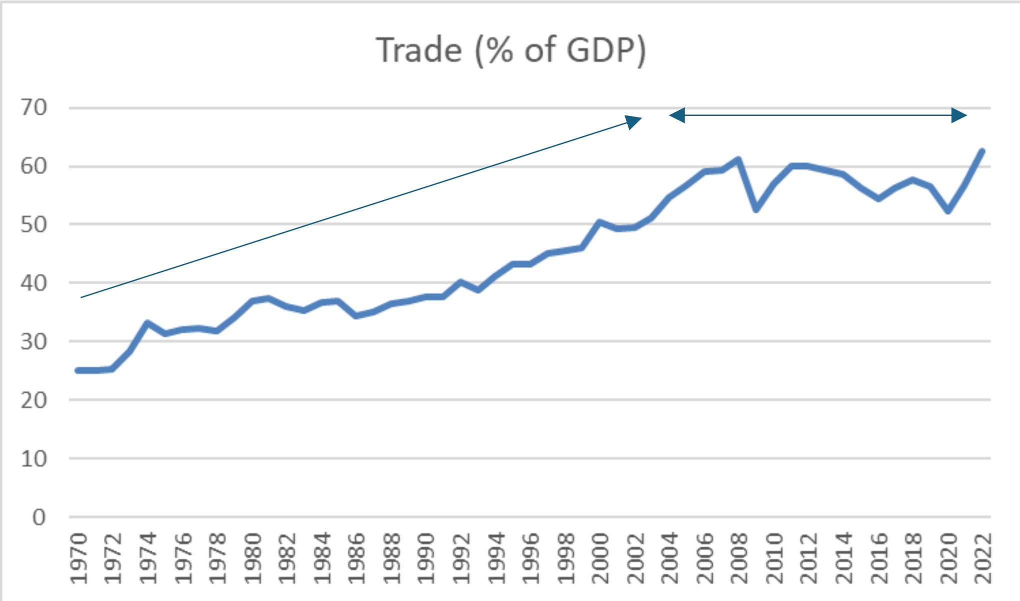
Trade is essential for increasing food security by ensuring a consistent variety of foods, improving the economic availability of food, and maintaining stable prices. Moreover, global trade allows regions to focus on producing items in which they have expertise, enhancing efficiency and reducing expenses (Burnett & Murphy, 2014). The movement of goods between countries facilitates a more reliable trading system crucial for maintaining stability and food security. However, trade itself has faced significant challenges in recent years, impacting food security globally.

Trade disruptions, such as the US-China trade war, the COVID-19 pandemic, and the Ukraine-Russia conflict, have profoundly affected global supply chains, leading to scarcity, higher prices, and food insecurity for millions. For instance, the US-China trade war resulted in increased tariffs on agricultural products, causing a drop in American soybean exports to China by nearly 50% in 2018 (Anggraini & Lidia, 2022). These interruptions have expanded beyond the involved nations, altering global trade patterns and resulting in the formation of new trade blocs. Such realignments fracture established trade networks, complicating international trade logistics and increasing costs. Countries outside the immediate conflict zones have implemented sanctions or tariffs in solidarity with their allies, further disrupting global trade flows. For example, the imposition of sanctions on Russia has not only affected Russian agricultural exports but also led to increased prices and shortages of key commodities in Europe and beyond.

The COVID-19 pandemic has significantly exacerbated challenges within the food industry and global trade. Lockdown measures, movement restrictions, and shifts in consumer behavior disrupted agricultural production, processing, distribution, and trade networks (Rahimi et al., 2023). Labor shortages, particularly in the United States, led to a sharp decline in fruit and vegetable harvesting, leaving millions of pounds of produce unharvested due to a lack of migrant labor. Additionally, processing facilities faced temporary closures and reduced operational capacity, further straining supply chains. Distribution networks were hindered by travel restrictions, resulting in delays and bottlenecks. Countries with limited domestic agricultural production became increasingly vulnerable, and low-income households experienced rising food prices and reduced availability. According to the FAO, food prices surged by over 30 percent globally during the pandemic's peak, pushing millions more into food insecurity.

Figure 1.3

Trade (% of GDP)



Source: World Development Index (2024)

By examining trade openness as a percentage of GDP, distinct trends reveal ongoing challenges over time. From 1992 to 2005, the index rose significantly, marking a period of substantial growth in trade openness, driven by globalization, trade liberalization, and the establishment of international trade agreements like the North American Free Trade Agreement (NAFTA) and the formation of the World Trade Organization (WTO). Technological advancements in transportation and communication also facilitated this growth, with container shipping revolutionizing global trade logistics.

In contrast, the period from 2006 to 2022 shows a relatively stable trend with less pronounced increases, highlighting the problems facing trade. The global financial crisis of 2008-2009 dampened international trade, leading to reduced demand and tighter financial conditions. Although a recovery followed, the growth in trade openness was not as robust as in the previous period. Rising protectionist sentiments and trade tensions, such as the US-China trade war, introduced further uncertainties to the global trade environment, with global merchandise trade growth slowing to 1.2% in 2019, the lowest rate since the global financial crisis.

Additionally, structural changes in the global economy, particularly the shift towards service-oriented economies, contributed to moderated growth in trade as a percentage of GDP. Services tend to be less tradable than goods, resulting in a slower increase in trade openness as economies develop. Finally, the unprecedented disruptions caused by the COVID-19 pandemic in 2020-2021 further impacted trade networks, exacerbating the challenges facing global trade and food security. A study estimated that by the end of 2021, global merchandise trade was still 5% below pre-pandemic levels, highlighting the long-lasting effects of these disruptions on international trade dynamics.

In conclusion, while trade has historically been a vital component in addressing food insecurity by ensuring a stable supply of food and enhancing economic accessibility, recent disruptions have exposed significant vulnerabilities within global trade systems. The challenges posed by the US-China trade war, the COVID-19 pandemic, and the Ukraine-Russia conflict have led to increased prices, supply shortages, and heightened food insecurity for millions, particularly in low-income countries that rely heavily on imports. The fluctuations in trade openness as a percentage of GDP reflect these ongoing issues, with a notable decline in growth rates due to protectionist policies, economic downturns, and structural shifts towards service-oriented economies. As nations grapple with the consequences of these disruptions, it becomes increasingly clear that a reevaluation of trade strategies is essential to foster resilience in food systems and ensure equitable access to food in the face of climate change and other emerging global challenges.

1.2 Problem Statement

Food security has gathered significant attention as a paramount global issue, drawing the focus of stakeholders ranging from policymakers to humanitarian organizations. While in the past, food security was generally perceived as abundant and dependable, the current landscape tells a different story. At the meantime, this deterioration in food security comes when the world grapples with the challenge of climate change. Climate change acts as an external and uncontrollable force that exacerbates existing vulnerabilities within food systems. Its impacts, ranging from erratic weather patterns to extreme events like droughts and floods, pose significant threats to agricultural productivity and food availability. As a result, the convergence of declining food security and the adverse effects of climate change paints a bleak picture for global food resilience.

It is notable that even by 2024, the exacerbating effects of climate change on global food security have become increasingly apparent. Rising temperatures, attributed to climate change, have wrought havoc on agricultural systems worldwide, leading to a myriad of challenges. Lakshmi et al. (2024) highlights that many crops have specific temperature thresholds for optimal growth. As temperatures rise beyond these thresholds, crop yields can significantly decline. For instance, a 1°C increase in temperature can reduce yields of staple crops like wheat and maize by 6% to 10%. Besides, changes in the timing of crop growth, modified rainfall patterns, and a surge in severe weather events have directly impacted agricultural output. Researchers such as Edmond and Geldard (2024) underscore the severity of these impacts, noting widespread decreases in crop yields and quality due to heat stress, water scarcity, and heightened pest activity. Additionally, the melting of glaciers and polar ice caps has led to rising sea levels and the salinization of coastal lands, further hindering food production. These impacts disproportionately affect at-risk populations, particularly in developing nations, resulting in scarcities, fluctuating prices, malnourishment, and economic insecurity.

Throughout history, trade has been a vital tool in improving global food security by enabling the distribution of resources and broadening the variety of food supplies. A recent study highlighted that trade openness has a positive and significant effect on food security in developing countries. Specifically, it found that a 1% increase in trade openness corresponds to an approximate 0.0518 improvement in the Global Food Security Index score (Algifahri & Heriqbaldi, 2023). The research on trade dynamics within the ASEAN region indicates that countries that embraced greater trade openness experienced an average increase in agricultural exports by about 15% over five years (Ghosh & Ghoshal, 2019). This statement also proved to be useful in enhancing food security which is hurt by the drastic climate change. This is due to the fact that climate change can impact the accessibility and standard of locally grown food, creating challenges for communities to fulfill their dietary requirements. Trade can assist in bridging these disparities and guaranteeing individuals' access to a broad range of healthy food options by enabling access to food from different areas (Berkum, 2021). However, a concerning trend has emerged in recent times, with many countries increasingly turning inward and adopting protectionism that restrict international trade. These measures are implemented either voluntarily or under external pressure, exacerbating the challenges faced by global trade networks.

To elaborate further, throughout the years there are several external factors that leading the collapsing of trade in the global economy. In 2018, the onset of the trade war between China and the United States further compounded the challenges facing global trade. During trade war, trade between the two countries was significantly affected as both sides-imposed tariffs on each other's goods. Besides, the global trade has also been greatly affected by the Covid-19 pandemic in 2019. At the time being, most of the countries are forced to close themselves from the external trade activities for the sake of their citizens' health and mitigate the spread of the virus. The pandemic has led to disruptions in international transport and logistics, resulting in increased trade costs and reduced global trade (Vo & Trần, 2021). Moreover, immediately following the disruptions caused by the COVID-19 pandemic, which significantly hampered global trade, the geopolitical conflicts between Ukraine and Russia occurred in 2022 (Pohl et al., 2023). These countries as being the main exporters of energy and agriculture sector, play a vital role in the global trade.

To sum up, even though trade has always been important for food security, the changes in global trade patterns require a re-evaluation of its effectiveness. Climate change impacts can disturb both local production and global trade paths, leaving nations heavily dependent on international trade at risk of greater food insecurity. While trade can be utilized among nations to solve food insecurity, there are disruptions on the world trade making the existing pattern to be complicated than before. There is an urgency in studying and solving this issue as food security, climate change, and the openness of global trade are becoming increasingly severe and are expected to become unsustainable if left unaddressed. Failure to act decisively will result in exacerbated food insecurity, heightened vulnerability to climate-related disasters, and further disruptions to global trade networks.

1.3 Research Objectives

1.3.1 General Objective

Food security is an ongoing global issue, creating an urgent need to examine the underlying causes and address food insecurity. Therefore, we aim to study the factors determining food security, exploring key influences such as economic, environmental, and social dynamics. Additionally, we will assess the effectiveness of current solutions in light of changes in the economic environment, ensuring that strategies remain adaptable and relevant in addressing this critical challenge.

1.3.2 Specific Objectives

1. To investigate the impact of climate change on food security
2. To investigate the effect of trade openness on food security
3. To investigate whether trade openness can mitigate the effects of climate change on food security

1.4 Research Questions

1. How does climate change have an impact on food security?
2. How does trade openness affect the food security?
3. How does trade openness mitigate the effects of climate change on food security?

1.5 Significance of Study

Our study addresses critical challenges countries are facing in preventing food insecurity through two main factors – trade openness and climate change. By studying the intersection between the two factors, we can determine how countries should act in policy-making to maintain food security levels in respective countries. Food security is a global concern that is closely related to the United Nations Sustainable Development Goals (SDG), particularly Goal 2 which aims to end world hunger. By aligning our research towards this goal, our study could contribute towards the global effort in addressing the challenges faced in food security problems. By aligning our study with SDG Goal 2, we aim to offer valuable contributions to ongoing global initiatives focused on eradicating hunger. Our research findings can support policymakers in crafting evidence-based strategies to manage the risks posed by climate change and trade dependencies. These strategies will help governments better understand the trade-offs and synergies between economic integration and environmental sustainability, empowering them to make informed decisions to strengthen food security.

With the escalation of geopolitical tensions, like the Ukraine conflict, the effects on worldwide food security are becoming more evident. Global food supply chains are disturbed by conflicts, demonstrating how geopolitical instability can cause significant disruptions in food availability. In this scenario, having open trade is essential because it enables nations to broaden their food resources and enter global markets, thus stabilizing supply chains. Nevertheless, the advantages of trade openness may be compromised by increasing protectionism and trade barriers stemming from geopolitical conflicts, highlighting the importance of this factor in ensuring a country's ability to uphold food security amidst global challenges. Given these shifting dynamics, the findings of previous research on trade openness and food security may no longer be fully applicable in today’s rapidly changing world. The growing influence of geopolitical factors on trade relations calls for a re-examination of past conclusions and the development of more adaptive strategies to navigate these emerging risks.

Current research on food security tends to focus on either trade openness or climate change in isolation, with few studies examining the combined impact of both factors on the food security issue. Our study aims to fill this gap by investigating the relationship between trade openness, climate change, and food security, exploring how these two critical variables interact with each other and whether they have positive or negative effects on global food security. Understanding these relationships is essential to reveal the complex interplay between economic policies and environmental pressures, offering a more comprehensive and realistic perspective on the challenges faced by countries in today's world. By analysing both trade openness and climate change together, our research will provide deeper insights into how these factors contribute to or undermine food security. This holistic approach is critical for identifying sustainable solutions that account for the interconnected nature of global trade systems and environmental changes..

Also, our study would contribute greatly to developing countries, particularly middle-income countries as our study will be on the global perspective in which we will investigate food security problem according to different regions with different income level as previous studies only focuses the food security impact to either developed or underdeveloped countries.

1.6 Scope of Study

This research aims to explore the global relationship between food security, trade openness, and climate change, with a focus on providing a thorough analysis of food security trends across 151 countries over a 20-year period from 2001 to 2020. By examining the impact of trade openness, which reflects a country's integration into the global economy, and the influence of climate change, which poses significant challenges to food production, the study will offer critical insights into the factors shaping food security on a global scale. To better understand both the specificity and universality of food security challenges, the research will incorporate case studies from a diverse range of countries. These case studies will illustrate how different nations are affected by and respond to trade and climate factors, highlighting the varying degrees of vulnerability or resilience. This approach allows for a nuanced understanding of the food security problem, recognizing that while certain patterns may be global, local and regional contexts play a significant role in shaping outcomes.

CHAPTER 2: LITERATURE REVIEW

2.1 Review of Theories and Concepts

2.1.1 Neo-Malthusian Theory

Neo-Malthusianism is a gloomy evaluation of the relationships between resources, economic growth, and population that is based on Thomas Malthus' theories (Mellos, 1988). Malthus believed that the availability of food, energy, and water would eventually constrain economic and population expansion. With the population expansion of the 1940s, this theory started to gain traction. Experts concluded that these would subsequently constrain population growth.

Since the mid-twentieth century, the world population has more than tripled. Over the next 30 years, the world population is projected to increase by about 2 billion, from the current level of 8 billion to 9.7 billion in 2050, with a peak of about 10.4 billion by the mid-1980s. This extraordinary population growth is the result of a combination of factors, including the increasing number of persons of reproductive age, the continuing increase in human longevity, the accelerating pace of urbanisation and the growing rate of population mobility (United Nations, 2022). As rapid economic and population growth outstrips the availability of resources, it will eventually lead to food insecurity. Population growth implies an increase in the labour force available for production, thereby increasing the gross domestic product (GDP).

In many cases, the amount of arable land remains constant. However, as the economy grows, the demand for arable land increases, as more land is needed to grow crops to meet the population's demand for commodities. In addition, agricultural land may be overused due to increased urbanisation brought about by rapid population growth. It has been found that the greater the pressure on land use, the more inadequate the food supply, while on the contrary, the lesser the pressure on land, the easier it is to secure the food supply due to the negative relationship between pressure on land and food sufficiency (Putri et al., 2019).

The dependency theory can support the discrepancy between food security, GDP per capita, and trade openness. Dependence on exports of low-value commodities from developing countries functions to other developing countries can hinder GDP per capita because marginalized countries earn less from trade, reducing the ability to improve food security. The tendency of capital from countries with an advantage in trade openness to move into marginalized countries and concentrate on industries that exploit natural resources, as well as the dependence of marginalized countries on core countries, all combine to worsen national food insecurity.

2.1.2 The Greenhouse Theory

Extreme weather events, such as droughts and floods, have become more frequent because of climate change. This has led to a decline in food production and quality, an increase in the spread of pests and a greater risk to global food security, endangering the food supply chain (Xiao & Cai, 2011). On the other hand, one of the principals currently recognized impacts of climate change is rising temperatures. The greenhouse effect refers to the long-term trend of increasing Earth's surface temperatures due to the increased concentration of greenhouse gases, such as carbon dioxide, in the atmosphere. As a result of these greenhouse gases, the atmosphere absorbs solar energy, warming the Earth's surface (Murray & Curren, 1993).

Unlike other businesses, agriculture depends more on natural circumstances for its output because most of its activities are done outside, but this also makes it susceptible to environmental consequences. Changes in precipitation patterns brought about by climate change exacerbate water scarcity and water-related disasters like floods and droughts (United Nations, 2022). The occurrence of disasters that destroy arable land used for crop production is linked to an uneven distribution of precipitation, which can affect the supply of food.

2.1.3 Dependency Theory

The concept of dependence has its roots in the disparity in growth between developed and developing nations, which arises from rich nations absorbing the resources of developing nations. The example of dependence incorporates both developed and developing nations (Perera, 2024). The reason developing nations continue to lag developed nations despite possessing an abundance of natural resources is that developed nations used colonialism to appropriate the resources of developing nations, resulting in poverty and dependence on the developed nations. According to the notion, undeveloped nations continue to be underdeveloped while profiting from their economic weariness. In contrast, developed nations take resources from emerging nations to amass wealth for their financial progress (Crossman, 2018).

Like this, certain impoverished emerging nations are more susceptible to global shocks due to their disadvantageous trade position and heavy reliance on commodity exports. When commodity prices fall, exports, jobs, and government revenue are all negatively impacted (UNCTAD, 2022). Dependency theory, on the other hand, emphasises how dependent developing nations are on imports and exports. When developing nations embrace trade liberalisation policies that are accessible to the outside world, this can result in the need for expensive imports of industrial products and low-cost raw material exports. Sociologists contend that long-term reliance is a permanent position from which the only way out is to abolish capitalism, even though trade exploitation stimulates economic progress. This is because developing nations that rely heavily on exports, particularly those of agricultural goods like spices, are vulnerable to the volatility of the global market and the dominance of wealthy nations. Therefore, economic expansion in developing nations reduces the capacity for GDP growth and is harmful to both overall economic development and the welfare of the populace.

2.2 Empirical Review

2.2.1 Different Definitions of Food Security

Food security is a complex and multifaceted concept that has been defined in various ways by researchers, organizations, and communities across the globe. These differing definitions reflect the diverse contexts and perspectives that shape how food security is understood and addressed. While the underlying goal of all definitions is to ensure that people have reliable access to sufficient, safe, and nutritious food, the specific focus and dimensions of food security can vary significantly. Understanding these definitions in detail, as well as the contexts in which they are developed, is crucial for grasping the full scope of food security challenges and solutions. By exploring these varied interpretations, we can better appreciate the diverse factors that influence food security and the tailored approaches needed to address them effectively. The different viewpoints of definitions are summarized in the table below.

Table 2.1

Definitions of Food Security

Researchers	Definitions
Naylor et al. (2023)	Defines food security as a situation where all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences.

Shatil and Islam (2024)	Food security is more practically defined by local communities as having a sufficient supply of rice to last the entire year.
Nguyen et al. (2023)	Emphasizes culturally relevant understandings of food security highlights the importance of traditional food practices, community well-being, and the intergenerational transfer of knowledge.
Poczta-Wajda (2018)	Advocate for a multidimensional approach to food security, incorporating not just availability and access, but also stability and utilization.
Pérez-Escamilla (2024)	Links food security with nutrition security, emphasizing that food security is a powerful social determinant of health.
Ferguson et al. (2023)	Emphasizes the importance of incorporating Indigenous ways of knowing, being, and doing in definitions of food security.

First and foremost, Naylor et al. (2023) defines food security as a situation in which all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life. This definition is widely recognized and serves as a foundational framework for global food security initiatives. It emphasizes four key pillars:

availability, access, utilization, and stability. This definition is comprehensive and holistic, addressing not only the quantity of food but also its quality and the stability of food supplies, which are crucial for sustaining long-term health and well-being.

Besides, different views arise when Shatil and Islam (2024) define food security in rural Bangladesh as having a reliable supply of rice throughout the year. For local communities, a sufficient amount of rice signifies food security. This practical definition reflects the daily realities and survival strategies of smallholder farmers who depend on rice for sustenance. It highlights the crucial role of staple crops in food security and the vulnerability of these communities to seasonal changes and agricultural challenges. Unlike broader definitions, this perspective is rooted in the community's immediate needs, emphasizing the importance of a single essential food resource.

Moreover, Nguyen et al. (2023) describe the Alaskan Inuit Food Security Conceptual Framework (AIFSCF) as a culturally relevant approach that emphasizes traditional food practices, community well-being, and environmental stewardship. Developed by the Inuit Circumpolar Council, this framework differs from Western definitions by incorporating the cultural and spiritual dimensions of food security essential to the Inuit way of life. It stresses the importance of preserving traditional knowledge, protecting the environment, and maintaining food sources that have supported the Inuit for generations. This perspective highlights the need to view food security through the lens of cultural identity, environmental changes, and overall community well-being.

Furthermore, Poczta-Wajda (2018) defines a multidimensional approach to food security as one that includes not only availability and access but also stability, utilization, and broader socio-economic and environmental factors. This approach recognizes the complexity of food security, acknowledging that it is shaped by a wide range of interrelated factors, including income levels, education, social networks, climate change, and market dynamics. By incorporating these dimensions, this perspective aims to provide a more comprehensive understanding of food security that goes beyond mere food availability. It suggests that effective food security strategies must address the underlying determinants of food insecurity, such as poverty, inequality, and environmental degradation, to create sustainable and resilient food systems.

Additionally, Pérez-Escamilla (2024) defines the Food and Nutrition Security Framework as linking food security with nutrition security, emphasizing food security as a key social determinant of health. This framework underscores the need for integrated approaches to monitor and evaluate food systems, taking into account their impact on health outcomes. It emphasizes that food security is not just about having access to sufficient food, but also about ensuring that the food is nutritious and contributes positively to overall health. This perspective draws attention to the importance of addressing malnutrition, dietary quality, and the broader health implications of food insecurity. It advocates for policies and interventions that consider both the quantity and quality of food, aiming to improve not only food security but also nutritional outcomes and public health.

Last but not least, Ferguson et al. (2023) define food security from Indigenous perspectives as integrating Indigenous knowledge, practices, and community-led initiatives. This approach advocates for community-led initiatives that respect traditional practices and address the unique challenges faced by Indigenous populations. Indigenous perspectives on food security often emphasize the significance of cultural identity, land rights, and autonomy in achieving food security. These communities view food security not just in terms of physical access to food, but also in relation to cultural practices, spiritual beliefs, and the intergenerational transmission of knowledge. This definition calls for a more inclusive understanding of food security that honours the cultural values and rights of Indigenous peoples, recognizing that food security is deeply intertwined with their identity, heritage, and connection to the land.

Each definition brings valuable insights into how food security is understood and addressed across different cultures and contexts. Incorporating these varied perspectives into studies and policies is crucial for developing holistic and effective strategies that address the unique needs and values of different communities. Recognizing the cultural, economic, and environmental dimensions of food security ensures that interventions are more inclusive, culturally sensitive, and responsive to the specific challenges faced by diverse populations, ultimately leading to more sustainable and equitable solutions.

2.2.2 Trade Openness and Food Security

Trade has long been recognized as a vital tool for addressing food security by enabling countries to access a diverse range of food items and stabilize local markets. Historically, trade has been instrumental in mitigating the effects of local crop failures and disruptions. For instance, Hertel et al. (2021) and Morton (2020) highlight that by sourcing food from various regions, countries can reduce their reliance on local production, thereby diversifying risk related to climate restrictions and other agricultural challenges. Baldos and Hertel (2015) further argue that a more open global trading system contributes to long-term food security by ensuring a steady supply of food items, even in the face of climate-related issues. Additionally, Leibovici and Adamopoulos (2024) show that diversifying food sources can enhance resilience against localized crop failures, leading to more consistent and reliable food supplies. Trade has thus been a crucial safety net, allowing countries to buffer against unexpected agricultural shortfalls and maintain a stable food supply.

Trade's role in improving food security has also been evident in its impact on food prices and economic growth. Berkum (2021) underscores how trade boosts global food availability and supports sustainable outcomes, particularly in low-income countries. Smith and Glauber (2019) note that global trade stabilizes food prices by balancing supply and demand across nations, with global production often being more stable than national production due to less correlated production shocks. Wang et al. (2023) and Martin (2019) emphasize that trade generates job opportunities and economic growth, which can uplift impoverished communities and enhance their access to essential goods. This economic boost not only supports food access but also fosters broader social development, linking economic prosperity with improved food security. Nonetheless, the benefits of trade are not equally distributed, and the most vulnerable populations often face barriers to accessing the advantages of global trade. Unequal access to trade opportunities can perpetuate or even exacerbate existing disparities in food security and economic well-being.

However, the once-beneficial role of trade in improving food security is increasingly becoming problematic. Trueblood and Shapouri (2001) raise concerns about the impact of trade liberalization on food security in developing countries, suggesting that an over-reliance on imports can undermine domestic production and stability. Similarly, Grassia et al. (2022) point out that low-income and food-insecure nations are vulnerable to external shocks in food trade, which can exacerbate their food security challenges. Such over-reliance can lead to a false sense of security, masking underlying vulnerabilities in domestic food systems. Additionally, fluctuating global trade policies and economic pressures can lead to unpredictable food availability and prices, further destabilizing food security in already vulnerable regions.

Moreover, Hellegers (2022) warns of the risks associated with dependence on specific countries, such as Russia and Ukraine, for food imports. Export restrictions by these countries can lead to increased global food prices and exacerbate food insecurity in dependent regions. Ritzel et al. (2024) further note that heavy reliance on food imports exposes nations to trade disruptions and price fluctuations. Political conflicts, natural disasters, or trade restrictions by exporting countries can lead to shortages and heightened food insecurity for importing nations. These vulnerabilities highlight the need for nations to diversify their food sources and develop more resilient domestic food systems. Relying heavily on a limited number of suppliers not only risks food shortages but also undermines the ability to respond effectively to global trade uncertainties.

Even though most pieces of literature gave different concerns when looking into the relationship between food security and trade openness, the majority of the researchers will agree that trade openness will affect food security positively; however, a small number of researchers gave an opposite view, where trade openness will negatively affect food security, as shown in the findings given by Sun and Zhang (2021). This was proven to be true by them as the effect of trade openness will only gave impact to food security positively in the long run. Kang (2015) also gave similar findings that trade openness negatively impacts food security, where he showed a similar explanation to Sun and Zhang who traced a U-shape relationship between trade openness and food security, where it will have a negative relationship in the early period and will only turn into a positive relationship in the long run.

In summary, while trade has historically been a key instrument for enhancing food security, its effectiveness is increasingly challenged by various issues. The benefits of trade in stabilizing markets and providing diverse food sources are being overshadowed by the vulnerabilities it creates. As global trade dynamics shift, it is crucial to reassess the role of trade in food security and explore complementary strategies to ensure resilience and sustainability in food systems. Adapting to these changes may involve investing in local agricultural capabilities, improving supply chain resilience, and developing strategies to mitigate the risks associated with global trade dependencies. Such measures are essential for creating a more secure and equitable global food system.

2.2.3 Climate Change and Food Security

There are many studies conducted particularly in examining the relationship between climate change and food security, in which most studies researchers agreed that climate change definitely will impact food security. Most studies concluded that climate change will have a significant and negative relationship with food security. Bandara and Cai (2014) concluded that food security is adversely affected by climate change through simulation results, which is consistent with previous studies' results. Dasgupta and Robinson (2022) also pointed out that most studies have shown a strong link between climate change and food security, which climate change can have negative impacts towards food security issues.

Besides, according to Lake et al. (2012), changes in the climate will affect food production in the future as producers have to adapt and change the way of producing crops with a different environment, which might have an impact on food safety as the nutritional value of the food produced might decrease. This will lead to worse food security issues, posing risks particularly on the vulnerable groups that already have insufficient amount of nutrition. Another study conducted by Devereux and Edwards (2004) also mentioned the disproportion in food security issues among countries with different climate, income level, and livelihood diversification, which will feel a greater impact caused by climate change among these countries with hotter and drier weather, lower income and lack of resources to transform the agriculture reliance will have the worst impact caused by climate change.

However, some studies showed that there is an insignificant relationship between climate change and food security when the study focuses on certain regions or countries. In a study, it was concluded that the impact of climate change on food security can be different across regions and countries, especially in developing countries that rely heavily on crops that require more rainwater (El Bilali et al., 2020). Another study also pointed out that climate change shows a significant relationship only in certain regions while not significant in other regions, with the impact of food security differing when using different indicators to represent climate change (Pickson et al., 2023).

This proved that food security issues are not equally prevalent in all countries and regions, especially in higher-income countries. Besides, an empirical study conducted in certain African countries has shown an insignificant relationship between temperature changes and crop yield, indicating that not all conditions caused by climate change will have a definite impact on food security issues (Mekonnen et al., 2021).

Among many of these previous findings, several scholars and researchers have pointed out that some gaps are not addressed in all of these research. Most studies focus heavily on the dual relationship between climate change and food security, while other factors that will impact the relationship between the two are rarely analysed (El Bilali et al., 2020). Other researchers also agree that the gap exists, pointing out that a multi-faceted approach must be undertaken while studying the relationship between climate change and food security, which will help (Saina et al., 2013). Moreover, current studies only focus on the relationship between changing climate and crop yields in the future, while missing out on the current problems and challenges that need to be addressed are also one of the limitations of many existing studies (Dasgupta & Robinson, 2022).

2.2.4 Climate Change and Trade Openness

Trade openness has been a significant driver of economic growth over the past 50 years, fostering global cooperation, facilitating cross-border trade in goods and services, and contributing to national development (WTO, 2024). However, the increase in trade has also led to complex environmental challenges, particularly concerning climate change, which has emerged as one of the most pressing issues of our time. The intricate relationship between trade and climate change presents both positive and negative impacts that require careful consideration.

On the positive side, trade openness reduces barriers and promotes global economic integration, which can lead to technological advancements that improve energy efficiency and environmental sustainability (Nam et al., 2024). For instance, as nations engage in trade, they often adopt more advanced technologies that can reduce carbon emissions and promote cleaner production methods, known as the technological effect. Additionally, trade can facilitate the exchange of environmentally friendly goods and services, contributing to global efforts to mitigate climate change.

However, the expansion of trade also brings negative environmental consequences. As trade increases, so does the production and transportation of goods, which can exacerbate environmental degradation and contribute to climate change. Countries seeking economic growth may focus on producing and exporting goods in which they have a comparative advantage, often at the expense of environmental sustainability. The international exchange of goods requires extensive transportation services, which are a significant source of carbon emissions.

Empirical studies have yielded mixed results on the relationship between trade openness and the environment. On one hand, trade can promote economic growth and technological advancement, which may lead to better environmental practices (Appiah et al., 2022). For example, emerging economic powers often exhibit high levels of trade, which has been a key factor in their development. On the other hand, the scale effect of increased trade openness leads to higher carbon emissions, contributing to climate change. This creates a complex relationship between trade and the environment, where the benefits of economic growth must be weighed against the environmental costs.

The study by Keen and Kotsogiannis (2014) emphasizes the interconnectedness of international trade and the environment, noting that as the world becomes more integrated, the pressures on policymakers and international organizations to address climate change intensify. The challenge lies in ensuring that trade policies are aligned with environmental sustainability goals, as not all countries are willing to bear the cost of improving the environment. In conclusion, while trade openness has been instrumental in driving global economic growth and development, it also poses significant environmental challenges, particularly concerning climate change. The relationship between trade and climate change is multifaceted, with both positive and negative aspects. To address these challenges, comprehensive policies that balance economic growth with environmental sustainability are essential. By understanding the complex interplay between trade and the environment, policymakers can develop strategies that promote both economic and environmental well-being.

2.2.5 Controlled Variables

The inclusion of control variables in our regression model is essential for accurately representing real-world dynamics and enhancing the precision of our estimates. By accounting for factors that may influence food security, we can ensure that our analysis more faithfully reflects the complexities of the issue. In our study, we include control variables such as population growth, arable land, GDP growth, and employment in agriculture. Each of these variables is carefully selected for its significant role in shaping food security, allowing for a more comprehensive and reliable assessment.

2.2.5.1 Population Growth

Population growth is a crucial factor in determining a country's capacity to provide sufficient and reliable food for its population. As the population increases, the demand for food resources rises significantly (Schneider et al., 2011). Miladinov (2023) argues that population growth can enhance food security by driving economic growth in agriculture, leading to more investments in farming methods, infrastructure, and technology to boost food production. Pimentel et al. (1997) similarly highlight the role of population in adopting innovative agricultural practices to sustain food quality amid growing demand.

Alexandratos (2005) explores how population growth impacts agricultural employment, increasing labour needs in countries with rapid population growth. This expansion in agricultural jobs, especially in rural areas, is seen as a means to improve living standards and food security. Oloni et al. (2017) and Thurlow et al. (2019) also support the idea that population growth drives labor demand in agriculture, creating employment opportunities that help secure a stable income and support daily food needs.

However, some studies present a different view. Lemaire et al. (2014) and Ramankutty et al. (2018) argue that population growth increases the demand for food production, leading to environmental degradation from expanded agriculture. This environmental impact poses long-term challenges for agriculture. Bellemare (2015) discusses how high food prices driven by large populations have led to riots and political instability across various regions, worsening food insecurity due to decreased investments during political unrest.

2.2.5.2 Arable Land

Weather, land, and water are critical components in the agricultural system that supports food security, with arable land playing a key role in maintaining a stable food supply (Chen et al., 2019). However, rapid global population growth has intensified the demand for arable land. Abebe (2024) notes that urbanization and industrialization, driven by population growth, have converted agricultural land to non-agricultural uses, reducing farmland and straining the global food supply. As a result, this reduction leads to lower food production, higher prices, and increased food insecurity, especially in urban areas. Additionally, Pravalie et al. (2021) highlight the global degradation of arable land due to drought and vegetation loss, further undermining agricultural productivity and contributing to food insecurity.

Moreover, Khan et al. (2019) argue that food security is influenced by multiple factors beyond arable land, including income, national conflicts, education, and corruption. Thus, even with sufficient farmland, low-income households may still face food insecurity due to affordability issues. Building on this, Herrera et al. (2021) emphasize that both agricultural practices and socio-economic factors, such as household size and education levels, play significant roles in determining food security.

2.2.5.3 GDP Growth

Świetlik (2018) highlighted a strong correlation between food security and economic development, particularly in developed countries. He emphasized that higher GDP per capita growth leads to improved food security by enhancing food availability and stability. This underscores the critical role of sustained economic growth in ensuring consistent access to sufficient and nutritious food.

Yılmaz and Günal (2023) supported this by showing that in 14 OECD countries, higher GDP growth rates significantly reduced the risk of food insecurity. They emphasized the importance of economic growth in preventing food insecurity by enabling investment in agricultural infrastructure and ensuring equitable food distribution. Similarly, Yaseen (2019) found that GDP growth in developing countries boosts food production and security, as it allows for better agricultural practices and improved food access.

Olofin et al. (2015) also demonstrated a statistically significant link between income growth and food security, noting that increased income directly enhances food security by enabling households to afford more diverse and nutritious diets. This relationship shows how economic growth can sustain both agricultural development and population health.

2.2.5.4 Employment in Agriculture

When examining the relationship between employment in agriculture and food security, researchers often focus on how agricultural work can improve household livelihoods, enabling better access to food. Bolarinwa et al. (2021) found that agricultural commercialization significantly impacts food security, as increased employment in this sector boosts household welfare, thereby ensuring food security for workers. Many studies also explore how income from farming reduces food insecurity in low-income or rural areas. For instance, research on rural sub-Saharan Africa by Dzanku (2019) revealed a strong statistical link between off-farm income and food security, particularly in regions with high food insecurity risks. Similarly, a study in Vietnam by Duong et al. (2021) showed that off-farm employment enhances household welfare by increasing income, lifting families out of poverty, and securing their food needs.

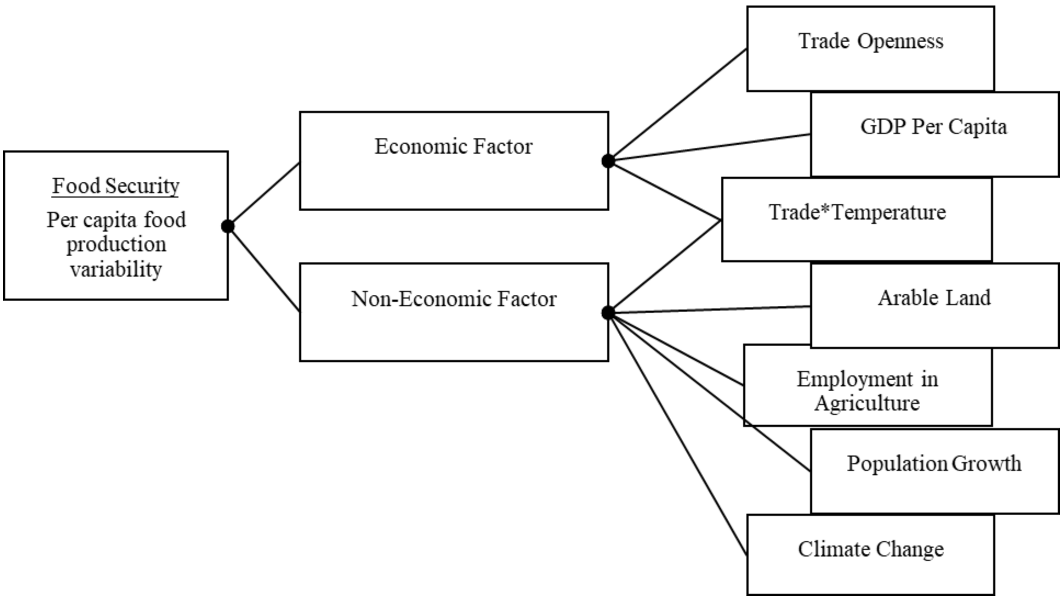
In developing countries, the relationship between agricultural employment and food security also extends to urban agriculture. Zezza and Tasciotti (2010) highlighted that urban agriculture significantly contributes to household food security, involving 10% to 70% of urban households in the workforce. Mozumdar (2012) further emphasized the importance of agricultural productivity in developing countries, noting that it provides employment to large segments of the population, directly impacting food security.

2.3 Conceptual Framework

In this research, Figure 2.1 illustrates an example of control variables (population growth, arable land, GDP per capita and employment in agriculture) and independent variables (trade openness and climate change) used to examine food security.

Figure 2.1

Conceptual Framework



2.4 Research Gap

In recent years, the relationship between trade openness and food security, especially in the face of adverse climate change, has become an increasingly important topic of study. Trade openness has the potential to either mitigate or exacerbate food security risks, depending on how it interacts with various regional factors. However, a significant research gap exists as the majority of studies have concentrated on specific geographical regions or a limited number of countries. This narrow focus creates a challenge for researchers and policymakers alike, as the findings from these studies may not be fully applicable to other regions with different economic structures, agricultural practices, and climate vulnerabilities. For instance, a policy that enhances food security in a trade-dependent island nation might not yield the same results in a landlocked country with a different set of trade and agricultural dynamics.

The selective approach of concentrating on specific regions limits the ability to generalize findings to a broader context. This is particularly problematic because the impact of trade openness on food security is highly context-dependent, varying widely across different regions due to factors such as climate variability, levels of development, and trade policy frameworks. For example, regions that rely heavily on imports for food security might experience different outcomes from trade openness compared to regions with robust domestic agricultural sectors. By focusing on only a few regions, existing studies risk overlooking critical nuances, leading to an incomplete understanding of how trade policies can be leveraged to enhance food security globally. This gap in research not only undermines the robustness and completeness of the findings but also raises concerns about the accuracy and applicability of these findings across different contexts.

Besides, the existing research extensively documents the positive relationship between trade openness and the alleviation of food insecurity. Historically, increased trade openness has been viewed as a catalyst for economic growth, improved agricultural productivity, and better food distribution across the globe. Past researchers such as Ushachev et al. (2022) and Fan et al. (2023) have concluded that by lowering trade barriers, countries can achieve greater food security by accessing a wider variety of food products at lower prices, and by benefiting from international agricultural innovations and investments. However, this findings may not be appropriate in today's context as several challenges arise lately.

Recent global events have significantly altered the landscape of international trade and introduced new challenges to the established understanding of trade openness as a driver of food security. The COVID-19 pandemic disrupted global supply chains, leading to shortages of critical food supplies and revealing vulnerabilities in highly interconnected trade networks. Additionally, the China-US trade war has led to increased tariffs and restrictions, particularly on agricultural products, thus impacting global food prices and availability. The Ukraine-Russia conflict has further complicated international trade dynamics, especially in the context of grain exports, as both Ukraine and Russia are major global suppliers of wheat and other essential food commodities.

In response to these crises, there has been a noticeable shift toward protectionism. Countries are increasingly adopting policies to protect their own food supplies and reduce dependency on foreign trade. This trend towards protectionism raises critical questions about the continued efficacy of trade openness in ensuring food security. The current body of research primarily focuses on the benefits of trade openness for food security under relatively stable global conditions. However, the recent geopolitical and economic disruptions highlight the need to reassess this relationship. Specifically, there is a lack of comprehensive studies examining whether the principles of trade openness that held true in the 20th century are still valid in the current context marked by frequent and severe global disruptions. Therefore, the purpose of our study is to investigate if the relationship between trade openness and food security still holds amidst these challenges, aiming to fill the research gap.

CHAPTER 3: METHODOLOGY

3.1 Introduction

In this study, our main goal is to assess the cause-and-effect relationships between the main independent variables, climate change, trade openness, and the interaction variable between climate change and trade openness, with other controlled variables including GDP per capita, population growth, arable land, and agricultural employment, and their impact on food security. To achieve this, secondary data collection methods were employed. The data used in this study were primarily sourced from the World Development Indicators (WDI) database and Food and Agricultural Organisation of the United Nations statistics database (FAOSTAT). In addition, academic articles and books were consulted to further enrich the study's foundation.

Our dataset covers 151 countries over 20 years, from 2001 to 2020. However, not all countries have complete data for the full period, and this has been accounted for in the analysis. The purpose of this chapter is to provide an overview of the data sources and econometrics methods used for gathering and analysing the data, ensuring that the findings are reliable and aligned with the research objectives.

Table 3.1

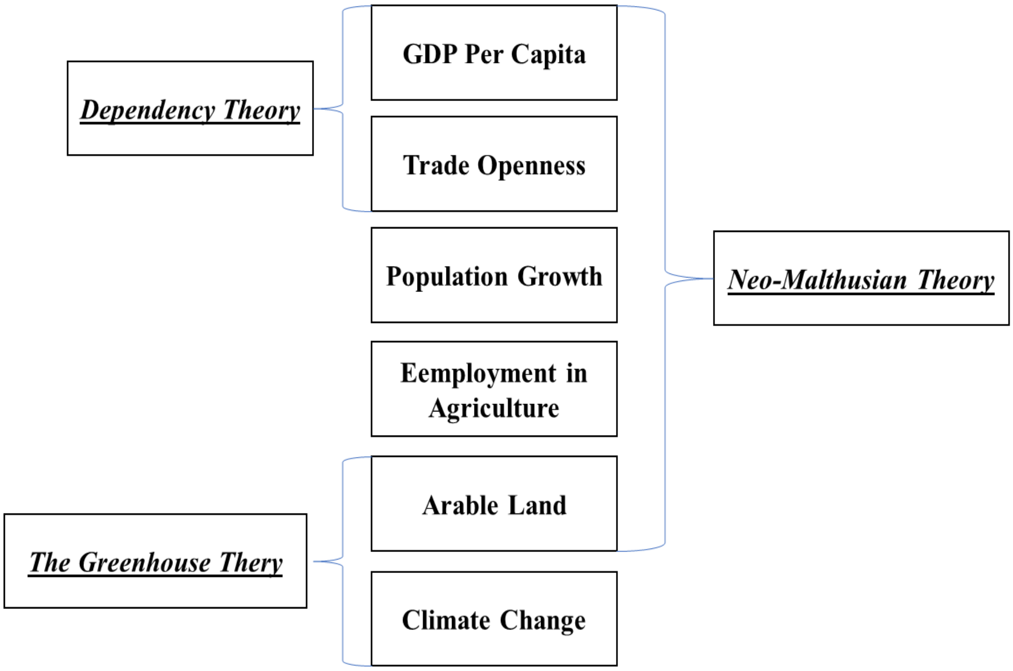
List of Countries/Regions/Territories Selected in Our Study

Albania	France	Niger
Algeria	French Polynesia	North Macedonia
Angola	Gabon	Norway
Argentina	Gambia	Oman
Armenia	Georgia	Pakistan
Australia	Germany	Panama
Austria	Ghana	Paraguay
Azerbaijan	Greece	Peru
Bahamas	Guatemala	Philippines
Bahrain	Guinea	Poland
Bangladesh	Guinea-Bissau	Portugal
Barbados	Haiti	Qatar
Belarus	Honduras	Republic of Korea
Belgium	Hungary	Republic of Moldova
Belize	Iceland	Romania
Benin	India	Russian Federation
Bhutan	Indonesia	Samoa
Bolivia	Iran	Saudi Arabia
Bosnia and Herzegovina	Iraq	Senegal
Botswana	Ireland	Serbia
Brazil	Israel	Sierra Leone
Brunei Darussalam	Italy	Slovakia
Bulgaria	Jamaica	Slovenia
Burkina Faso	Japan	Solomon Islands
Cabo Verde	Jordan	South Africa
Cambodia	Kazakhstan	Spain
Cameroon	Kenya	Sweden
Canada	Kuwait	Switzerland
Central African Republic	Kyrgyzstan	Syrian Arab Republic
Chad	Laos	Tajikistan
Chile	Latvia	Thailand
China, Hong Kong SAR	Lebanon	Timor-Leste
P. R. China	Lesotho	Togo
Colombia	Libya	Tonga
Comoros	Lithuania	Tunisia
Congo	Luxembourg	Türkiye
Côte d'Ivoire	Madagascar	Turkmenistan
Croatia	Malaysia	Uganda
Cuba	Mali	Ukraine
Cyprus	Malta	United Arab Emirates
Czechia	Mauritania	United Kingdom
Congo	Mauritius	United Republic of
Denmark	Mexico	Tanzania
Dominican Republic	Mongolia	United States of America
Ecuador	Montenegro	Uruguay
Egypt	Morocco	Uzbekistan
El Salvador	Namibia	Vanuatu
Estonia	Nepal	Viet Nam
Eswatini	Netherlands	Zambia
Fiji	New Zealand	Zimbabwe
Finland	Nicaragua	

3.2 Theoretical Model

Figure 3.1

Theoretical Model



This study's theoretical framework draws on established theories to understand how various factors influence food security. Key variables such as climate change and trade openness, are incorporated with controlled variables often used by other studies including GDP per capita, population growth, arable land, and employment in agriculture, with the primary foundation of our model based on the model of Neo-Malthusianism, complemented by aspects of dependency and greenhouse theories.

Neo-Malthusian theory emphasizes the strain that rapid population growth places on limited resources like arable land, increasing demand for food and agricultural output. In this model, population growth is a key variable, reflecting this pressure on resources, while arable land represents the limited capacity for food production. Employment in agriculture is also important, as a larger workforce in agriculture can help meet rising demand, but it is constrained by available land. Trade openness can mitigate some of these pressures by allowing food imports, though it may also expose countries to global market risks. GDP per capita is included to reflect the economic capacity of a nation to invest in food security solutions. We also draw trade openness and GDP per capita variables from dependency theory, which emphasizes the role of global economic relationships in shaping resource availability. Trade openness captures a country's integration into global markets, potentially alleviating food shortages through imports but also exposing nations to market volatility. GDP per capita represents economic development, indicating a country's ability to invest in food security initiatives and infrastructure.

A critical element of our model is the interaction between temperature change and trade openness. This interaction term allows the study to assess whether trade mitigates or amplifies the effects of climate change on food security. In some cases, trade can help buffer the impacts of climate change by enabling countries to import food, while in others, it might increase vulnerability to global supply chain disruptions. Hence, we also use greenhouse theory, which uses both climate change and arable land as its variables where employment in agriculture is included to capture the workforce's role in food production. Changes in agricultural employment may directly influence food security, particularly in regions highly dependent on agriculture.

Overall, our model integrates key insights from Neo-Malthusianism, dependency theory, and greenhouse theory to provide a comprehensive understanding of the factors influencing food security. By combining these variables, the model seeks to evaluate the effects of climate change, trade, and economic development on food security outcomes across different countries.

3.3 Empirical Model

Our study suggests an empirical model that links food security to climate change and trade openness. In our research, we will use the Food Production Variability Per Capita to act as the proxy for Food Security. To conduct our research, we used the data obtained from the Food and Agriculture Organization (FAO) and the World Development Index from World Bank from year 2001 to 2020.

Climate change and trade openness are the main focuses of our study. Hence, temperature change, trade, and a variable multiplying both temperature change and trade are used as the main independent variables, followed by few controlled variables including population growth, arable land, Gross domestic product (GDP) per capita and employment in agriculture to form the econometric model as below:

Food Security = f (Temperature, Trade, Temperature × Trade, Population, Land, GDP, Employment)

$$\begin{aligned} lnFOOD_{it} = \beta_0 &+ \beta_1 lnTEMP_{it} + \beta_2 lnTRADE_{it} + \beta_3 lnTEMPTRADE_{it} \\ &+ \beta_4 lnPOP_{it} + \beta_5 lnLAND_{it} + \beta_6 lnGDP_{it} + \beta_7 lnEMPLOY_{it} \\ &+ \varepsilon_{it} \end{aligned}$$

Equation 3.1

Where,

$FOOD_{it}$ = Per capita food production variability (constant 2014-2016 thousand int$ per capita) at time t

$TEMP_{it}$ = Temperature change (°c) at time t

$TRADE_{it}$ = Trade (% of GDP) at time t

$TEMPTRADE_{it}$ = Temperature change multiply with trade at time t

POP_{it} = Population growth (annual %) at time t

$LAND_{it}$ = Arable land (hectares per person) at time t

GDP_{it} = Gross Domestic Product per capita (constant 2015 US$) at time t

$EMPLOY_{it}$ = Employment in agriculture (% of total employment) at time t

ln = natural logarithm

ε_{it} = Error term at time t

i = Selected 151 countries

t = 2001, 2002, 2003, …, 2020

The presence of these four controlled variables will help us to make our results more reliable with the inclusion of factors that are generally recognized by other researchers that significantly influence food security in the long run.

3.4 Data Description

Table 3.2

Proxy Used for Each Variables

Acronym	Variables	Proxy Used	Source of Data
FOOD	Food Security	Per capita food production variability (constant 2014-2016 thousand int$ per capita)	FAOSTAT**
TEMP	Climate Change	Temperature change on land (°c)	FAOSTAT**
TRADE	Trade Openness	Trade (% of GDP)	WDI*
TEMPTRADE	Climate Change x Trade Openness	Temperature change on land (°c), Trade (% of GDP)	FAOSTAT**, WDI*
LAND	Arable Land	Arable land (hectares per person)	WDI*
POP	Population Growth	Population growth (annual %)	WDI*
GDP	GDP per Capita	GDP per capita (constant 2015 US$)	WDI*
EMPLOY	Agricultural Production Factor	Employment in agriculture (% of total employment)	WDI*

**WDI (World Development Index, World Bank)*
***FAOSTAT (Food and Agriculture Organization Statistics)*

Per capita food production variability: Food production per capita is individual over time. Food is not only a necessity for human survival, but also a driving force for national economic growth. Therefore, a flourishing agricultural sector brings with it opportunities and favorable economic consequences, all which stem from an increase in per capita food production (Shaikh, 2024). Studies have shown that food production per capita directly affects the growth of a country's own gross domestic product (GDP) and the contribution of the Ministry of Agriculture and is a key determinant of a country's economic prosperity. High per capita food production ensures a stable food supply and reduces dependence on imports from other countries; on the other hand, it stimulates a country's export potential and increases trade opportunities (by exporting surplus food and increasing foreign exchange earnings). Indicators can be used to analyses long-term trends in the stability of a country's food supply, and since fluctuations in food supply have a knock-on effect on vulnerable households, understanding the extent of fluctuations can help policymakers to act.

Population growth: We selected 151 countries from the World Bank organization. The experiment uses data from 2001 to 2020. Population growth is a demographic phenomenon of global social and economic relevance. In population ecology, population growth is the study of fluctuations over time in the size of a given population within a given geographical area. Population growth is influenced by factors such as fertility and mortality, and the population growth rate is the average change in the population over a given period. A higher growth rate indicates a larger population; a negative growth rate indicates a smaller population. As with other growth rates, the population growth rate is calculated by subtracting the current population size from the previous population. Divide this by the last size population. Multiply by 100 to find the percentage (Foflonker, 2024). Understanding population growth trends can explain population growth's impact on food security.

Arable Land： We selected a representative subset of 151 countries from the World Bank Group. The experiment involves data from 2001 to 2020. According to the definition of the Food and Agriculture Organisation of the United Nations, arable land includes temporary crop land, which includes double cropping areas (counted once). It refers to land used primarily for agricultural purposes, such as growing crops and grazing livestock. In addition, land used for markets or vegetable gardens and land temporarily left fallow under certain conditions (not exceeding five years) can also be considered as arable land (World Bank, 2024). Analysing the amount of arable land helps to clarify the relationship between arable land and its impact on food security.

Gross domestic product (GDP) per capita: We selected 151 countries from the World Bank organization. The experiment uses data from 2001 to 2020. GDP per capita refers to the measure of a country's total economic output divided by its population, showing the average income or economic productivity per person. It is a measure of the quality of life in a nation, with greater figures typically suggesting a stronger economy. GDP per capita is determined by adding up the value created by all producers in an economy, either at basic prices (minus net taxes on products) or at producer prices (including net taxes on products paid by producers, but not including sales or value-added taxes). This metric is frequently shown in a widely used currency like US dollars for global comparisons, while also taking into account inflation to show accurate purchasing power. Analyzing GDP per person allows for evaluating the financial welfare of citizens in a country and making comparisons between various areas or time periods.

Employment in Agriculture: We selected 151 countries from the World Bank organization. The experiment uses data from 2001 to 2020. The agricultural sector includes farming, hunting, forestry, and fishing activities. Agricultural employment is defined as the number of persons in the working-age population who are engaged in agriculture-related work, services, or industries for remuneration. This includes persons engaged in any paid production of goods or provision of services, temporary absence from work, or work under other working time arrangements. It does not include the labour of persons under working age (child labour). This includes persons directly involved in agricultural production, such as farmers, herders, fishermen and foresters, who are directly involved in agricultural activities such as planting, breeding, fishing, or logging. According to two indicators published by the International Labor Organization through the World Bank, the total labour force and the proportion of the labour force engaged in agriculture (Ritchie & Roser, 2024). By calculation, the number of people engaged in agriculture is equal to the total labour force multiplied by the proportion of the labour force engaged in agriculture. Analyses of agricultural employment have helped to clarify the relationship between agricultural employment and food security.

Trade Openness: We selected 151 countries from the World Bank organization. The experiment uses data from 2001 to 2020. Trade openness is defined as the ratio of exports plus imports to GDP. Trade openness reflects how open a country is to external markets and how willing it is to trade with other countries. At the same time, trade integration is also a factor that influences currency crises; it increases a country's ability to fulfill its external commitments and reduces the probability of currency crises because it increases a country's export ratio and, thus, its ability to service its external debt, thus improving the stability of the country's economy and reducing the occurrence of external financial crises (Steiner, 2016). Analyses of trade openness have helped to clarify the relationship between trade openness and food security.

Climate Change: We selected 151 countries from the World Bank organization. The experiment uses data from 2001 to 2020.In 2013, the IPCC published a worldwide peer-reviewed assessment on the impact of human activities on climate change, coinciding with the release of its Fifth Assessment. The report's findings were unequivocal: climate change is an undeniable reality and human actions, particularly the emission of harmful gases resulting from the combustion of fossil fuels (coal, oil, gas), are the primary driver of this phenomenon (United Nations Environmental Programme, 2021). What are the repercussions and effects of climate change? Escalating occurrences of severe weather phenomena, elevating sea levels, and jeopardising agricultural and food security. climatic change can be measured by using climatic data collected from observatories to track changes in temperature (Pidcock, 2019).

3.5 Model Estimation

In our study, we recognize the importance of employing a diverse set of panel data models to ensure a comprehensive analysis of the relationships of the food security with the selected independent variables. The Pooled Ordinary Least Squares (Pooled OLS), Fixed Effects Model (FEM), and Random Effects Model (REM) each offer distinctive advantages and limitations thus we aim to navigate strategically to derive convincing conclusions.

3.5.1 Pooled Ordinary Least Squares (Pooled OLS)

The concept of Pooled OLS is explained within the context of panel data analysis. Pooled OLS is represented as a methodological approach that integrates data from distinct time periods into a unified unit, treating the combined dataset similar to a singular cross-sectional observation. Fundamentally, Pooled OLS operates under the assumption of homogeneity across entities, assuming no hidden entity-specific effects that might skew the analysis. It assumes uniform characteristics among the entities under study, thus simplifying the modeling process.

The Ordinary Least Squares (OLS) regression method relies on five core assumptions, as outlined by Berry (1993) and Wooldridge (2010). Firstly, linearity asserts that the dependent variable is a linear function of the independent variables and the error term. Exogeneity, the second assumption, stipulates that the expected value of the error term is zero, indicating no correlation with the regressors. The third assumption addresses the homoskedasticity of disturbances, meaning they have constant variance and are not related to each other (non-autocorrelation). Additionally, the observations on the independent variables are assumed to be fixed across repeated samples without measurement errors. Finally, the full rank assumption posits that there is no exact linear relationship among independent variables, precluding multicollinearity.

The basic equation for Pooled OLS can be written as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_k X_{k,it} + \mu_{it}$$

Where:

Y_{it} is the dependent variable for unit i at time t,

β_0 is the intercept,

β_1, β_2, …, β_k are the coefficients to be estimated,

$X_{1,it}$, $X_{2,it}$, …, $X_{k,it}$ are the independent variables for unit i at time t,

μ_{it} is the error term.

However, Pooled OLS does not adequately account for the potential correlation of error terms within the same cross-sectional unit over time, leading to inefficient estimates and biased standard errors. This can be problematic, especially for panel data where observations may be correlated within the same unit. To solve this problem, two common techniques are used, including the Fixed Effects Model (FEM) and the Random Effects Model (REM).

3.5.2 Fixed Effect Model (FEM)

The Fixed Effect Model (FEM) in statistics is a method used to control for unobserved individual heterogeneity in panel data analysis. It assumes that each individual in the dataset has a unique intercept that remains constant over time, effectively capturing individual-specific characteristics that persist across observations (Zulfikar & STp, 2018). A key assumption of this model is that these individual-specific effects are uncorrelated with the independent variables, indicating no systematic relationship between these effects and the explanatory variables. By doing so, the fixed effect model helps in accounting for factors specific to each individual that may influence the dependent variable.

The equation for FEM can be written as:

$$Y_{it} = \alpha_i + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_k X_{k,it} + \mu_{it}$$

Where α_i represents the fixed effect for unit i.

However, it has limitations, such as its inability to estimate the effects of time-invariant variables, as these are absorbed by the individual-specific effects. Additionally, the fixed effect model requires a large sample size to produce reliable estimates.

3.5.3 Random Effect Model (REM)

Random Effects Models (REMs) offer a distinct approach in statistical analysis by explicitly modelling variations in effects across space and time. In contrast to Fixed Effects models, which assume a single effect affecting all higher-level units uniformly, REMs provide a framework to capture nuanced variations. They are particularly useful when the variable of interest is extraneous to the error term, indicating that individual characteristics have no effect on the regressors and are uncorrelated (Bell & Jones, 2014).

One of the key assumptions of REM is that the unobserved individual effects are uncorrelated with the regressors, making them suitable for situations where the variable of interest can be considered as randomly assigned. This flexibility allows REM to accommodate varying effects across entities and time, thereby offering a comprehensive analysis compared to FEM. Moreover, REMs excel in handling data exhibiting group-level variation, enabling a deeper understanding of the underlying data structure.

The equation for REM can be written as:

$$Y_{it} = \alpha_i + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_k X_{k,it} + \mu_{it}$$

Where α_i represents the random effect for unit i.

However, REM have its limitations. The exclusion of fixed effect dummies could potentially introduce bias in slopes, thereby affecting the precision of estimates. REM may also not be appropriate when the variable of interest is not independent of the error term, thereby violating a crucial assumption of the model.

3.6 Model Selection

When deciding between Pooled OLS, FEM and REM for panel data analysis, it's common practice to employ a combination of tests to assess the suitability of each model. The Likelihood Ratio (LR) test, Hausman specification test, and Breusch-Pagan (BP)/LM test are indeed among the most frequently used tests for this purpose.

3.6.1 Poolability F-test

Poolability F-Test can be utilized in panel data analysis to choose between the Pooled OLS and Fixed Effects Model (FEM). Poolability F-Test is a valuable tool for assessing whether the individual-specific effects are significant, thereby determining the appropriateness of pooling the data. The test compares the fit between the pooled OLS model and the FEM by testing whether the coefficients on individual-specific dummies are equal to zero. The null hypothesis assumes that Pooled OLS is preferable, while the alternative hypothesis suggests that FEM is preferable. If the poolability F test yields a statistically significant result, it indicates that FEM fits the data significantly better than Pooled OLS, hence researchers would generally reject the null hypothesis and decide to use the Fixed Effects Model. Conversely, if the poolability F test does not produce a significant result, researchers may conclude that the Pooled OLS model is more adequate for the data.

3.6.2 Breusch-Pagan Lagrangian Multiplier Test (BPLM)

The Breusch-Pagan Lagrangian multiplier (BPLM) test is a technique often used in panel data analysis to detect heteroscedasticity, which occurs when the variance of the error terms does not remain constant across observations (Peterson et al., 2012). This test is very useful when deciding between whether to use Pooled OLS and REM model. The test consists of regressing the squared residuals from the initial regression on the explanatory factors to see if there is a systematic link between the variance of the error terms and the independent variables. The null hypothesis of the test indicates that there is no heteroscedasticity in the data, making Pooled OLS the preferred option. In contrast, the alternative hypothesis indicates that heteroscedasticity exists, implying that REM is preferable. A statistical significant result indicates that the null hypothesis will be rejected and the alternative will be accepted, making REM model a better fit, while if the results of this test is insignificant, the null hypothesis will be accepted and pooled OLS will be the preferred model.

3.6.3 Hausman Specification Test

The Hausman Specification Test is a crucial tool in panel data analysis, particularly for comparing the consistency and efficiency of FEM and REM. Its primary objective is to examine whether the random effects assumption holds by examining the correlation between individual-specific effects and the regressors (Frondel & Vance, 2010). The null hypothesis of the test suggests that the individual-specific effects are uncorrelated with the regressors and REM model is more preferable, while the alternative hypothesis suggests that there is a correlation between them, indicating FEM is a better-fit model. A statistically significant result from this test provides evidence in favour of the alternative hypothesis and the null hypothesis will be rejected, indicating that FEM is the preferable model to be used for the panel data. On the contrary, insignificant result from this test will conclude that REM is the better model to be used.

3.7 Diagnostic Checking

Diagnostic Checking is a crucial step in our study which will run through several tests to capture the observed panel data. It can be used to check for multicollinearity, autocorrelation, normality distribution and more problems that need to be avoided in our study. A few diagnostic tests will be run, including panel unit root test, autocorrelation test, heteroskedasticity test, groupwise heteroskedasticity test, and cross-sectional dependence test of. All tests will be conducted using EViews 12 and Stata 17 to obtain the results.

3.7.1 Panel Unit Root Test

Panel unit root test is a common empirical test used by researchers to determine whether the data is stationary. There are two generations of tests within the panel unit root test. In the first generation of tests, it assumes that cross-section units are independent. In the second generation of tests, the assumption is exempted, and cross-sectional dependence is allowed (Tugcu, 2018). To assess the stationarity of the data in the panel unit root test, four tests were employed: the Levin, Lin, and Chu (LLC) test, the Im, Pesaran, and Shin (IPS) W-stat, the ADF-Fisher Chi-square, and the PP-Fisher Chi-square. These tests are performed in both intercept and intercept & trend for level and first difference.

3.7.1.1 Levin, Lin, and Chu (LLC) Test

The Levin, Lin, and Chu (LLC) test is used to determine whether panel data is stationary or exhibits a unit root. It assumes that all cross-sectional units share the same autoregressive parameter and that the data is cross-sectionally independent. The LLC test evaluates whether the time series data in each cross-sectional unit follow a similar autoregressive structure. However, this test's assumptions can limit its applicability: the assumption of cross-sectional independence may not hold in practice, and the requirement for homogeneity of autoregressive parameters might not be appropriate if there are significant differences across units.

3.7.1.2 Im, Pesaran, and Shin (IPS) W-Stat

The Im, Pesaran, and Shin (IPS) W-stat test extends the LLC test by allowing for different autoregressive parameters across individual time series, thus accommodating more heterogeneity. It assumes that the errors are independently and identically distributed within and across cross-sectional units. Despite its flexibility in handling heterogeneous autoregressive parameters, the IPS test still relies on the assumption of cross-sectional independence, which may not be realistic in datasets where cross-sectional units influence each other.

3.7.1.3 ADF-Fisher Chi-Square Test

The ADF-Fisher Chi-Square test aggregates p-values from individual Augmented Dickey-Fuller (ADF) tests conducted on each time series within the panel. It forms a chi-square statistic to test for unit roots across the panel. The test assumes that p-values from the ADF tests are independent and that cross-sectional units are independent of one another. The assumption of p-value independence can be problematic if there is cross-sectional dependence, potentially affecting the robustness of the results.

3.7.1.4 PP-Fisher Chi-Square Test

The PP-Fisher Chi-Square test combines p-values from Phillips-Perron (PP) tests across multiple time series into a chi-square statistic. Like the ADF-Fisher test, it assumes that the p-values are independent and that the time series data across cross-sectional units are independent. The test's effectiveness can be limited by the same issues of cross-sectional dependence and the independence of p-values, which may not always be applicable in real-world datasets where cross-sectional units might be interconnected.

3.7.2 Wooldridge Test for Autocorrelation

The Wooldridge test is used to detect auto-correlation in panel data models. It tests whether the residuals are correlated over time within individual units. The null hypothesis assumes there is no auto-correlation problem in the model, vice versa for the alternative hypothesis. Statistically significant results indicate the null hypothesis being rejected, indicating there is auto-correlation problems in the model, hence, adjustments like using robust standard errors or different estimation techniques may be necessary to solve the problems.

3.7.3 Breusch-Pagan/Cook-Weisberg Test for Heteroskedasticity

The Breusch-Pagan/Cook-Weisberg test for heteroscedasticity problems in the model, which checks whether the variance of the residuals is constant across observations, which is an assumption in OLS regression. The null hypothesis assumes homoskedasticity in the model (constant variance), whereas the alternative hypothesis assumes heteroskedasticity in the model. If the result of the test is significant, null hypothesis will be rejected, and heteroskedasticity problem is present in the model. Researchers might need to use heteroskedasticity-robust standard errors in the model to solve this issue.

3.7.4 Modified Wald Test for Groupwise Heteroskedasticity

The Modified Wald test is used in panel data analysis to detect groupwise heteroskedasticity, which occurs when the variance of the errors differs across groups, such as individuals, firms, or countries. The null hypothesis assumes homoskedasticity, meaning the variance is constant across all groups, whereas the alternative hypothesis assumes heteroskedasticity in the model. A significant result from this test will result in the rejection of null hypothesis, indicating groupwise heteroskedasticity problem is present in the model. This suggests that different groups exhibit different levels of variability. In such cases, it’s crucial to adjust the model by using cluster-robust standard errors to obtain reliable and accurate estimates.

3.7.5 Pesaran's Test of Cross-Sectional Dependence

Pesaran's test is used in panel data analysis to assess cross-sectional dependence, which occurs when the residuals of different cross-sectional units (such as countries, firms, or regions) are correlated. The null hypothesis assumes that the cross-sectional units are independent of each other, while the alternative hypothesis assumes that they are dependent of each other. A statistical significant result will result in the rejection of null hypothesis, indicating there is cross-sectional dependence problem in the model. This suggests that external factors or common shocks may be affecting multiple units simultaneously.

CHAPTER 4: DATA ANALYSIS

4.1 Descriptive Statistics

In this study, we analyse data collected from 151 countries over a span of two decades, from 2001 to 2020, with a total of 2961 observations due to some omitted data. The primary objective of our descriptive statistical analysis is to explore the fundamental characteristics of the variables selected for the study. By calculating measures such as the mean, median, maximum, minimum, and standard deviation, we aim to provide a comprehensive overview of the data's central tendencies, dispersion, and overall distribution. Our main focus is on the dependent variable, food security which is represented by per capita food production variability. Additionally, we focus on two independent variables: trade openness, measured by trade as a percentage of GDP, and climate change, measured by temperature change. By analysing these variables, we aim to better understand their impact on global food security over time.

Table 4.1

Descriptive Statistics

Variables	FOOD	TEMP	TRADE	LAND	POP	GDP	EMPLOY
Mean	20.7118	1.0929	85.2158	0.2387	1.3727	13448.83	26.1975
Median	13.8	1.031	76.2147	0.1686	1.2463	5049.08	19.1378
Maximum	190.9	3.669	442.62	1.976	19.3604	112417.9	84.7269
Minimum	0.4000	-0.457	15.683	0.0003	-6.8521	322.4401	0.2058
Std. Dev.	21.7718	0.5481	48.3824	0.2491	1.5887	18232.4	22.3933
Jacque-Bera	16439.5***	278.9467***	22683.08***	20778.11***	76600.09***	4911.449***	296.9577***
Observations	2961	2961	2961	2961	2961	2961	2961

Note. FOOD – Per capita food production variability (constant 2014-2016 thousand int$ per capita), TEMP – Temperature change (°C), TRADE – Trade (% of GDP), LAND – Arable land (hectares per person), POP – Population growth (annual %), GDP – GDP per capita (constant 2015 US$), EMPLOY – Employment in agriculture (% of total employment)

The descriptive statistics of the variables FOOD, TEMP, TRADE, LAND, POP, GDP, and EMPLOY are summarized in Table 4.1 reveal significant disparities across the 151 countries studied.

For FOOD (per capita food production variability), the mean of 20.7118 is notably higher than the median of 13.8, indicating a right-skewed distribution influenced by a few countries with exceptionally high variability. For example, Paraguay in 2014 recorded a maximum value of 190.9, while Saudi Arabia's minimum value of 0.4 in 2009 reflects minimal variability. This stark contrast, with the maximum nearly 478 times greater than the minimum, highlights vast differences in food production stability. The high standard deviation of 21.7718 further emphasizes the significant dispersion, suggesting that factors such as climate variability, agricultural practices, and infrastructure play crucial roles in food production resilience across countries.

TEMP (temperature change) exhibits moderate variability, with a mean of 1.0929°C and a median of 1.031°C. The temperature change ranges from -0.457°C in Chile in 2007 to a maximum of 3.669°C in the Russian Federation in 2020. The standard deviation of 0.5481 indicates notable variability, reflecting how different climatic conditions and the impacts of climate change affect agricultural practices and food security in various regions.

Besides, TRADE (trade as a percentage of GDP) shows a mean of 85.2158% and a median of 76.2147%, with a wide range from 15.683% in Cuba in 2020 to 442.62% in Hong Kong in 2013. This disparity underscores significant differences in trade openness, influenced by government policies, economic structures, and geographical factors. The standard deviation of 48.3824 indicates substantial variability in trade dependence among countries, with some nations heavily reliant on trade for economic growth. The high dispersion of the sample data underscores the importance of determining the role of trade in influencing food security, as varying levels of trade openness can have differing impacts on different countries or regions.

Descriptive statistics for controlled variables highlight significant disparities in LAND, POP, GDP, and EMPLOY across the studied countries. Descriptive statistics for the controlled variables reveal significant disparities among countries. Starting with LAND (arable land per person), the average is 0.2387 hectares, though the distribution is right-skewed, ranging from nearly zero in Hong Kong to almost 2 hectares in Kazakhstan. This variation underscores the differences in agricultural capacity driven by geographic size and land management practices. Turning to POP (population growth rate), the mean is 1.3727%, but it spans from -6.8521% in Syria to 19.3604% in Qatar, reflecting diverse demographic trends and related challenges. Meanwhile, GDP per capita is highly skewed, with a mean of $13,448.83 and a range from $322.44 in the Democratic Republic of the Congo to $112,417.90 in Luxembourg, highlighting significant economic inequalities. Finally, EMPLOY (employment in agriculture) averages 26.1975%, varying from 0.2058% in Hong Kong to 84.7269% in Burkina Faso, indicating substantial differences in the significance of agriculture across countries.

Overall, the descriptive statistics reveal significant disparities across the variables, particularly in FOOD, TRADE, and TEMP. The extreme dispersion in these three main variables indicate substantial variability among the 151 countries studied, which is crucial for understanding the complex relationships between food security, trade openness, and climate change. Additionally, the controlled variables, including LAND, POP, GDP, and EMPLOY, further emphasize the diverse economic and agricultural contexts in which these countries operate. These disparities underscore the need for tailored approaches when analyzing the impact of these factors on global food security.

4.2 Panel Unit Root Test

In analyzing the long-run relationships between the chosen variables, it is essential to establish a robust regression model that accurately captures these dynamics. One critical assumption in regression analysis is the stationarity of the data, which implies that the statistical properties of the time series do not change over time. Non-stationary data can lead to spurious regression results, potentially misguiding interpretations and policy implications. To address this concern, we conducted a panel unit root test on our sample of 151 countries covering the period from 2001 to 2020. This test aims to determine the presence of unit roots in the time series data, indicating whether the series is stationary or requires differencing to achieve stationarity. By confirming stationarity, we enhance the reliability of our long-run regression model, providing clearer insights into the interactions among food security, trade, and climate change.

The four panel unit root tests used include Levin, Lin & Chu (LLC) t* Test, Im, Pesaran, and Shin (IPS) W-stat Test, ADF - Fisher Chi-Square Test, and PP - Fisher Chi-Square Test each have their own assumptions and limitations. The LLC t* test assumes a common unit root process across all panels, which can lead to biased results if the panels have heterogeneous dynamics. In contrast, the IPS W-stat test allows for individual unit root processes but may lack power with small sample sizes or significant cross-sectional dependencies. The ADF - Fisher Chi-Square test assumes independent time series drawn from a common distribution, making it sensitive to structural breaks, while the PP - Fisher Chi-Square test relies on the Phillips-Perron framework and assumes independent error terms, also being affected by structural breaks. Given these varying assumptions and limitations, employing multiple tests is crucial for a robust assessment of data stationarity, as they can provide complementary insights into the underlying dynamics. The tests are done in both intercept and intercept & trend form.

Table 4.2

Panel Unit Root Test for Level

Variables	Levin, Lin & Chu t*		Im, Pesaran and Shin W-stat		ADF - Fisher Chi-Square		PP - Fisher Chi-Square	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend
lnFOOD	-6.3928***	-5.5235***	-8.3593***	-4.7836***	528.063***	430.580***	426.589***	333.591***
lnTEMP	-20.8490***	-31.7815***	-16.9722***	-26.1235***	904.607***	1210.44***	1218.73***	1514.63***
lnTRADE	-3.9580***	-5.95.9***	-2.1835***	-2.5894***	380.330***	415.358***	368.723***	341.897**
lnTRADETEMP	-21.6685***	-31.6790***	-17.2215***	-26.2708***	916.307***	1217.37***	1276.52***	1509.26***
lnLAND	-3.9440***	-4.0905***	-10.4501***	-1.6156***	550.106***	411.036***	907.865***	322.367***
lnPOP	-8.1117***	-11.6904***	-8.9548***	-8.0289***	927.395***	573.213***	504.161***	306.135
lnGDP	-13.0232***	-0.1624***	-4.2045***	3.8593***	461.896***	337.443***	577.328***	221.489***
lnEMPLOY	-4.9779***	-4.1981***	4.5511	-0.7253	323.264	397.087***	394.812***	366.377***

Note. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

Table 4.3

Panel Unit Root Test for First Difference

Variables	Levin, Lin & Chu t*		Im, Pesaran and Shin W-stat		ADF - Fisher Chi-Square		PP - Fisher Chi-Square	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend	Intercept	Intercept & Trend
lnFOOD	-37.3637***	-30.7886***	-33.6161***	-25.3717***	1562.28***	1170.17***	2020.89***	1579.63***
lnTRADE	-33.9796***	-32.1196***	-30.1484***	-25.1846***	1624.13***	1132.85***	1774.97***	1557.01***
lnTEMP	-53.1123***	-40.7731***	-53.0317***	-40.5868***	2536.16***	1837.31***	13999.8***	2996.82***
lnTRADETEMP	-51.7037***	-39.6898***	-52.4918***	-40.0684***	2515.25***	1813.05***	14659.0***	3001.64***
lnLAND	-13.8346***	-75.4244***	-24.6458***	-27.2781***	1222.88***	1019.78***	1704.48***	1219.87***
lnGDP	-10.4990***	-8.8738***	-13.1677***	-9.7486***	742.620***	623.312***	725.584***	626.109***
lnEMPLOY	-22.8280***	-18.4691***	-25.3116***	-17.8595***	1244.13***	934.356***	2195.95***	1305.30***
lnPOP	-23.2087***	-22.6864***	-21.6464***	-17.2806***	1334.24***	826.680***	1569.58***	768.718***

Note. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

Table 4.2 presents the panel unit root test results for the levels of the logged variables, including lnFOOD, lnTRADE, lnTEMP, lnTRADETEMP, lnLAND, lnGDP, lnEMPLOY, and lnPOP. These variables are essential to our analysis, focusing on food production variability, trade, temperature changes, land availability, economic output, employment in agriculture, and population growth. In contrast, Table 4.3 displays the results for the first differences of these logged variables, offering insights into their dynamic behavior over time. All variables have been transformed into their natural logarithmic form to enhance consistency and comparability across the dataset. This transformation stabilizes the variance and normalizes the distribution of the data. The results from both tables indicate that all variables are stationary, as confirmed by various tests, including Levin, Lin & Chu t*, Im, Pesaran and Shin W-stat, and the Fisher-type tests.

The stationarity of the all the variables implies that the time series data do not exhibit a unit root in their levels or first differences, indicating that their statistical properties, such as mean and variance, remain constant over time. This is crucial for our long-run regression model, as non-stationary data can lead to spurious regression results. Since the variables can be used in their level form, categorized as I(0), the confirmation of stationarity enhances the reliability of our subsequent analysis and strengthens our ability to draw meaningful conclusions about the relationships between food security, trade openness, and climate change.

4.3 Correlation Analysis

In this section, we conduct a correlation analysis among the natural logarithmic forms of all variables in our sample data, including lnFOOD, lnTRADE, lnTEMP, lnTRADETEMP, lnLAND, lnGDP, lnEMPLOY, and lnPOP. This analysis aims to identify the strength and direction of relationships between these variables, providing insights that are essential for developing a robust long-run regression model. One critical assumption in regression analysis is that the independent variables should not exhibit strong correlations with one another, as this can lead to multicollinearity, which distorts the estimates of the regression coefficients and complicates the interpretation of results. By examining the correlation coefficients, we can detect any potential multicollinearity issues before proceeding with the regression analysis. Addressing multicollinearity ensures the validity and reliability of our model, allowing for a more accurate assessment of the relationships among food security, trade openness, climate change, and other economic factors.

Table 4.4

Correlation Analysis

Variables	lnFOOD	lnTRADE	lnTEMP	lnTRADETEMP	lnLAND	lnGDP	lnEMPLOY	lnPOP
lnFOOD	1							
lnTRADE	0.0514***	1						
lnTEMP	0.1244***	0.1084***	1					
lnTRADETEMP	0.1321***	0.2211***	0.9886***	1				
lnLAND	0.4558***	-0.2659***	0.0496***	0.0171	1			
lnGDP	0.2076***	0.2941***	0.1699***	0.2085***	-0.2492***	1		
lnEMPLOY	-0.0954***	-0.3492***	-0.2063***	-0.2516***	0.3873***	-0.8910***	1	
lnPOP	-0.2639***	-0.0975***	-0.1023***	-0.1155***	-0.1951***	-0.2410***	0.1883***	1

Note. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

The correlation analysis presented in Table 4.4 reveals the linear associations among various variables related to food production, trade, temperature, land, GDP, employment, and population growth. Notably, employment and GDP in natural log form exhibit a high negative correlation of -0.8910. This strong inverse relationship suggests that as employment in agriculture increases, GDP tends to decrease, indicating potential structural shifts in the economy where labour may be moving away from agricultural sectors toward other industries. One possible reason for this high correlation could be that economies with a large agricultural workforce often have lower levels of industrialization, resulting in lower GDP per capita.

To address potential multicollinearity, we considered removing lnEMPLOY from the analysis. However, upon reassessment, we found that the coefficients and signs of the remaining variables remained consistent, indicating that the removal of lnEMPLOY would not significantly impact the overall model. Consequently, we do not suspect a multicollinearity problem, as the high correlation observed between employment and GDP does not undermine the integrity of our regression analysis. This allows us to proceed confidently with our long-run regression model, ensuring that our results will provide valid insights into the relationships among food security, trade openness, and climate change.

The correlation between lnTRADETEMP and lnTEMP is exceptionally high at 0.9886, indicating a strong linear relationship between the two variables. This correlation is however expected because lnTRADETEMP is an interaction term derived from TRADE and TEMP, capturing the combined effects of trade and temperature on food security. Such a close correlation near 1 does not pose a multicollinearity issue; instead, it reflects the inherent relationship between these variables, which is crucial for our analysis. By including this interaction term in our regression model, we can effectively examine how variations in temperature impact trade dynamics and, subsequently, per capita food production variability. Thus, this high correlation serves to enhance our understanding of the interplay between trade and climate variables, rather than detracting from the reliability of our regression analysis.

4.4 Pooled OLS, Fixed Effect Model (FEM), Random Effect Model (REM), and Diagnostic Tests

Table 4.5

Long Run Regression and Diagnostic Tests

	Homogenous Panel	Heterogenous Panel	
	POLS	FEM	REM
c	0.6510***	0.1096	0.2331
	(0.1708)	(0.3105)	(0.2621)
lnTEMP	-0.5503	-0.2785	-0.2688
	(0.3878)	(0.2811)	(0.2794)
lnTRADE	0.1443***	-0.0382	0.0025
	(0.0469)	(0.0613)	(0.0567)
lnTRADETEMP	0.33383*	0.1522	0.1539
	(0.2022)	(0.1460)	(0.1452)
lnPOP	-0.3861***	0.0618	0.0272
	(0.0812)	(0.0746)	(0.0726)
lnLAND	0.4173***	0.3382***	0.3922***
	(0.0141)	(0.0631)	(0.0377)
lnGDP	0.2259***	0.3247***	0.2948***
	(0.0232)	(0.0632)	(0.0472)
lnEMPLOY	0.0441	0.0869	0.0771
	(0.0282)	(0.0662)	(0.0546)

No. of Obs	2961	2961	2961
R^2	0.3352	-	-
Adj. R^2	0.3336	-	-
R^2-Within	-	0.0202	0.0196
R^2-Between	-	0.3891	0.4102
R^2-Overall	-	0.3024	0.3183
Wald chi^2	-	-	161.76***
Specification tests			
Poolability F test	-	33.59***	-
BPLM test	-	-	10360.36***
Hausman test	-	11.83	-
Diagnostic tests			
Wooldridge Auto-correlation test			495.158***
Heteroskedasticity test			9.39***
Groupwise heteroskedasticity test			4330.86***
Cross-sectional dependency test			2.326**

Note. The standard error values are shown in the parentheses. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

As shown in Table 4.5, we started to use the pooled ordinary least square (POLS) model to estimate our data initially, in which most of the variables significantly influenced food security (FS). However, using pooled OLS model to estimate our data has one major limitation, which is it ignores the specific effects of the model such as cross-sectional and time-specific effects. Hence, pooled OLS may produce results that are inaccurate and misleading. Thus, we then used panel data models, including fixed effect model (FEM) and random effect model (REM) to examine food security.

Besides, F-test was conducted between the three models to select the best model used to estimate food security. It is found that through poolability F test, the null hypothesis is rejected, which indicates that the fixed effect model (FEM) is better to be used than pooled OLS model for our panel data. Then, we also conducted Bruesch Pagan Lagrangian multiplier (BLPM) test between pooled OLS and random effect model (REM) to find the better model. It is found that the null hypothesis in this test is rejected, further showing that REM is the better model than pooled OLS used to estimate panel data. In addition, the Hausman test was used to test whether FEM or REM is the better model to explain the food security of our complex panel data set. It is found that the null hypothesis of our test is not rejected, indicating that the random effect model is more preferable to estimate our panel data. In short, these three tests concluded that the random effect model (REM) is a more accurate and convincing estimator of our data.

To obtain an accurate interpretation of our panel data, we must ensure that the estimator model we used is effective and valid. Several diagnostic tests were conducted to examine the model's validity, and whether it is affected by problems such as serial correlation, heteroscedasticity and cross-dependence. The results of the diagnostic test are shown in Table 4.4. In the case of serial correlation tests, the null hypothesis of the autocorrelation test is rejected, with the F-statistics (495.158) in this test being significant at the 1% level, indicating the presence of serial correlation in our data set. In the case of both heteroscedasticity and group-wise heteroscedasticity test, the chi^2 statistics (9.39 and 4330.86 respectively) in the model are significant at the 1% level, hence the null hypothesis is rejected, indicating the presence of heteroscedasticity in the data set. In the case of the cross-sectional dependence (CSD) test, the null hypothesis is rejected, with the F-statistics being significant at the 5% level, indicating presence of cross-sectional dependence in the data set.

Although through poolability F test, BPLM test and Hauman test, the random effect model (REM) is the most preferred model to interpret our data, the presence of cross-sectional dependence and heteroskedasticity problem in the data set greatly affect the conclusiveness of the model be used. Therefore, we adopt another estimator – the Driscoll-Kraay standard error estimator to run the data. The Driscoll-Kraay standard error estimator is particularly useful when there is heteroscedasticity and cross-sectional dependence. The Driscoll-Kraay estimator adjusts the standard errors to account for heteroscedasticity, ensuring that the statistical inferences are valid even when the variance of the errors differs across units or time periods. in panel data models. The Driscoll-Kraay standard error estimation is further explained below in section 4.5.

4.5 Driscoll-Kraay Standard Error Estimation

We use the Driscoll-Kraay standard error estimator to interpret food security because the models help to overcome cross-sectional and dependence problems in the dataset, which will be more decisive than other models. The results obtained from the Driscoll-Kraay standard error estimator are shown in Table 4.6, along with data estimated with adjusted standard errors using pooled OLS, fixed effect and random effect models. The results show that more variables are now insignificant in all three models of pooled OLS, FEM and REM. However, the Driscoll-Kraay standard error estimation model shows almost all significant variables. It shows that the coefficients of lntrade, lntradetem, lnland, lngdp, and lnemploy are positive, while coefficients of lntem and lnpop are negative, consistent with our expectations.

Table 4.6

Long Run Regression with Adjusted Standard Error

	POLS	FEM	REM	Driscoll-Kraay estimator
c	0.6510	0.1096	0.2331	0.6510**
	(0.6394)	(0.5905)	(0.4432)	(0.2289)
lnTEMP	-0.5503	-0.2785	-0.2688	-0.5503
	(0.8672)	(0.3493)	(0.3524)	(0.3241)
lnTRADE	0.1443	-0.0382	0.0025	0.1443**
	(0.1502)	(0.0985)	(0.0889)	(0.0526)
lnTRADETEMP	0.3338	0.1522	0.1539	0.3338*
	(0.4451)	(0.1835)	(0.1842)	(0.1792)
lnPOP	-0.3861*	0.0618	0.0272	-0.3861***
	(0.2325)	(0.0689)	(0.0633)	(0.1213)
lnLAND	0.4173*	0.3382**	0.3922**	0.4173***
	(0.0511)	(0.1531)	(0.0620)	(0.0122)
lnGDP	0.2259**	0.3247**	0.2948**	0.2259***
	(0.0946)	(0.1441)	(0.0904)	(0.0238)

lnEMPLOY	0.0441 (0.1049)	0.0869 (0.1224)	0.0771 (0.0963)	0.0441 (0.0322)
No. of Obs	2961	2961	2961	2961
R^2	0.3352	-	-	0.3352
Adj. R^2	-	-	-	-
R^2-Within	-	0.0202	0.0196	-
R^2-Between	-	0.3891	0.4102	-
R^2-Overall	-	0.3024	0.3183	-
Wald chi^2	-	-	57.87***	-

Note. The standard error values are shown in the parentheses. * Indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

The results confirm that the per capita food production variability increases with the increase of trade openness, the interaction between trade openness and temperature, arable land, gross domestic production (GDP) per capita and employment in the agricultural sector, while food production variability decreases with the increase of change in temperature and population growth, keeping all other factors constant.

Using the results obtained from Table 4.6 on the Driscoll-Kraay estimator model, the coefficient suggests that an increase in the change in temperature by 1% decreases the per capita food production variability by 0.5503% at a very high level of significance, ceteris paribus. Whereas if the trade openness increases by 1%, per capita food production variability increases by 0.1443% at a 5% level of significance, ceteris paribus. If the interaction between trade openness and temperature increases by 1%, per capita food production variability increases by 0.3338% at a 10% level of significance, ceteris paribus. Besides, the population growth increases by 1% if per capita food production variability decreases by 0.3861% at a 1% level of significance, ceteris paribus, while the arable land increases by 1% when per capita food production variability increases by 0.4173% at a 1% level of significance, ceteris paribus. Also, a 1% increase in the gross domestic product (GDP) per capita will increase per capita food production variability by 0.2259% at a 1% level of significance, ceteris paribus, whereas a 1%

increase in the employment in agriculture increases per capita food production variability by 0.0441% at a very high level of significance, ceteris paribus.

4.6 Study Findings

Table 4.7

Comparisons between Expected Relationship and Our Findings

Main Variables	Expected relationship between main variables & lnFOOD (Y proxy)	Research Findings
Trade Openness	Significant (Mixed relationships)	Significant (Positive)
Climate Changes x Trade Openness	Significant (Mixed relationships)	Significant (Positive)
Climate Change	Mixture of Significant & Insignificant	Insignificant

For trade openness, we expected it to have a statistically significant relationship with lnFOOD, and a positive relationship with food security. Our findings shown that trade openness has a significant positive relationship with lnFOOD, which is inconsistent with most findings of past studies, which shows negative relationship with food security. Similarly, we expected the interaction term – climate change x trade openness to have a statistically significant relationship with lnFOOD, and a positive relationship with food security. However, it shows positive relationship between the interaction term and lnFOOD, thus a negative relationship with food security, in contrast to most of the results. However, these two inconsistencies can be explained by the findings obtained by Sun and Zhang (2021) and Kang (2015) as our results only reflected the short-term effect between food security and trade openness.

For climate change, we expected it may have either significant or insignificant relationship with lnFOOD, and with food security as past studies shown mixed results depending on other factors. Our findings have shown an insignificant relationship, which can be supported by the findings conducted by El Bilali et al. (2020) and Pickson et al. (2023), which also concluded insignificant relationship between food security and climate change.

CHAPTER 5: CONCLUSION AND IMPLICATION

5.1 Summary of Statistical Analysis

This study utilized several analytical approaches, including the Pooled Ordinary Least Squares (OLS) model, the Fixed Effects Model (FEM), and the Random Effects Model (REM). To determine the most suitable model for our data analysis, we applied the Hausman test, the Poolability test, and the Breusch-Pagan Lagrange Multiplier (BPLM) test. Based on the results of these evaluations, the Random Effects Model (REM) was identified as the most appropriate model for this study.

To ensure the reliability and robustness of our results, we conducted a thorough comparison, analysis, and testing of the Pooled OLS, FEM and REM for potential econometric issues. This included applying the Wooldridge test for autocorrelation, heteroskedasticity tests, groupwise heteroskedasticity tests, and cross-sectional dependency (CSD) tests. The findings revealed that these models were impacted by econometric concerns such as autocorrelation, heteroskedasticity, within-group heteroskedasticity, and cross-sectional dependence.

To enhance the reliability of our inferences, Driscoll-Kraay standard error estimation approach is employed, given the results of the model specification tests. This method is particularly effective in addressing issues such as autocorrelation, heteroskedasticity, and cross-sectional dependence, providing robust standard errors that account for these econometric concerns. By utilizing the Driscoll-Kraay approach, we can obtain more reliable and accurate estimates, ensuring that the conclusions drawn from our analysis are more robust and credible.

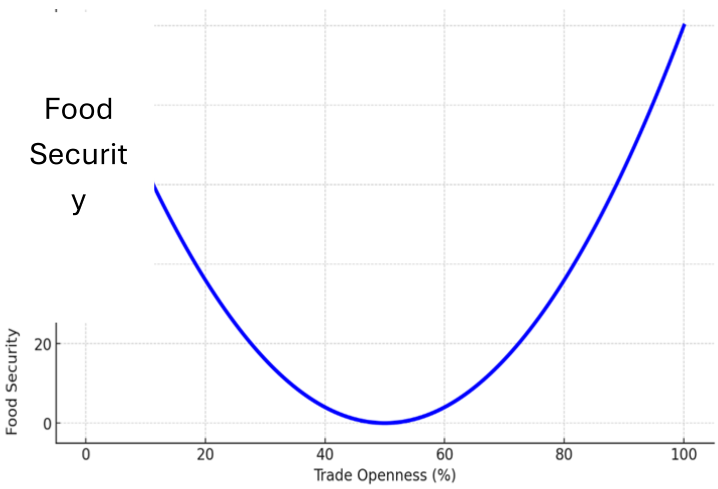
The main research objective was to determine whether trade openness could mitigate the adverse impacts of climate change on food security. However, our results indicate that trade openness may exacerbate these effects rather than alleviate them. This finding supports the hypothesis that trade liberalization could lead to changes in food output, potentially undermining food security. Additionally, the study uncovered a consistent and unexpected relationship between trade openness and the influence of climate change on food security, highlighting a complex interaction that warrants further investigation.

Additionally, the control variables in this study include both economic and non-economic factors that significantly influence food security. Variables such as gross domestic product (GDP) per capita, arable land area, and agricultural employment positively contribute to enhancing food security. In contrast, factors like temperature change and population growth have a negative impact on food security. The study's findings are consistent with these expected outcomes, reinforcing the understanding of how these variables affect food security dynamics.

5.2 Major Findings of the Study

Figure 5.1

U-shaped Relationship between Trade Openness and Food Security



This study delves into the supply side of food security, revealing that trade openness can negatively impact food stability. We employed per capita food production variability as a proxy, selected for its critical role in ensuring food security resilience, as outlined by the Food Systems Dashboard (2024). The findings suggest a U-shaped correlation between trade openness and food security stability, aligning with prior research by Sun and Zhang (2021) and Kang (2015). This implies that while trade openness may initially destabilize food security, there could be a turning point where further openness could potentially lead to stabilization, highlighting the complex nature of the relationship between trade policies and food stability.

The per capita change in food supply, which quantifies the amount of food available per person based on production and trade factors, serves as a crucial measure of a food system's resilience. A stable food system should be able to minimize supply fluctuations in response to unexpected events, such as economic shocks or natural disasters. Our study evaluates food security by examining these fluctuations, with a particular focus on stability. The results indicate that if increased trade openness leads to greater variability in per capita food supply, it can detrimentally affect food security by weakening the system's ability to consistently meet the population's food needs. This finding underscores the need for carefully balanced trade policies that consider the potential for increased volatility in food availability.

Initially, increased trade openness appears to negatively impact food security, particularly in countries that may lack a competitive edge in global markets. This suggests that trade openness might lead to a redistribution of global food production, where countries with comparative advantages in specific agricultural products benefit at the expense of others. These shifts can leave certain nations, especially those heavily dependent on food imports or facing structural economic challenges, more vulnerable to global inflation and other economic pressures, thereby exacerbating the adverse effects of trade openness on food security. This finding directly addresses our first research question and highlights the importance of considering local economic contexts in global trade discussions.

Our initial expectation was that climate change would have a significant negative impact on food security, as suggested by the negative coefficient for temperature change in our models. This expectation was based on the understanding that rising temperatures and other climate-related factors generally disrupt agricultural productivity, leading to reduced food production and availability. However, the model shows that the temperature change variable is statistically insignificant. This insignificance suggests that, contrary to our expectations, the relationship between climate change and food security is not as strong or direct as initially hypothesized. Thus, climate change itself is considered does not have any significant relationship with food security in our model. This finding directly addresses our second research question and highlights that climate change does not affect food security.

Conversely, the interaction between trade openness and climate change on food security presents a more complex picture than initially anticipated, as evidenced by the positive coefficient for temperature change in this context. Even though climate change itself is an insignificant variable, but the interactive term of trade openness and climate change appears to be significant. While trade openness generally promotes economic growth by increasing access to global markets, its benefits may be offset by the adverse effects of climate change. As temperatures rise, the ability of countries to produce and distribute food is compromised, which can undermine the potential benefits of trade in stabilizing food supplies. This interaction suggests that while trade can be a tool for enhancing food security, it must be managed carefully in the face of climate change to avoid exacerbating vulnerabilities. This finding directly addresses our third research question and highlights the importance of considering trade openness in addressing food insecurity caused by the climate change.

In summary, while trade openness has the potential to foster economic growth and enhance food security, its interaction with climate change introduces significant challenges that could undermine these benefits. The role of temperature change due to climate change does not significantly affect food security but when it comes to the interactive term, it appears to be significant. Therefore, it is crucial to consider the dynamic interplay between trade openness and climate change impacts when assessing the overall impacts on food security, ensuring that strategies are both resilient and adaptive to these evolving challenges.

5.3 Implications of the Study

Based on the findings of this study, which indicate that increased trade increased per capita food production variability, it is critical to make appropriate recommendations. These recommendations should focus on reducing the potential adverse effects of trade on food production and increasing overall food security. Food security can be achieved through a combination of self-sufficiency and trade liberalisation. Therefore, two key policy implications emerge including optimising trade policy frameworks to balance openness and protection as well as strengthening domestic agricultural assistance and promoting technological progress.

5.3.1 Optimising Trade Policy Frameworks to Balance Openness and Protection

Research findings indicate that trade openness can negatively impact per capita food production, potentially due to import competition undermining local agricultural output. Therefore, it is essential for countries to balance market openness with effective trade protection mechanisms, especially for critical food production sectors. Implementing strategic tariff barriers or differentiated tariffs for various agricultural products can help safeguard vital domestic crops while encouraging agricultural diversification. Such measures can protect local food producers from excessive international competition and reduce the risk of anti-dumping in the short term.

Besides, free trade policies may also have adverse effects on specific regions. In the short term, countries facing food insecurity might rely heavily on imports to meet their needs. For exporting countries, this approach can help manage domestic oversupply, stabilize the national food supply, reduce price volatility, and lower the cost of maintaining food reserves. However, prolonged dependency on imports can create vulnerability, as countries might become over-reliant on foreign sources, undermining their self-sufficiency. While comparative advantage promotes specialization and economies of scale, it is crucial to evaluate whether self-sufficiency can mitigate this dependency effectively.

Furthermore, food self-sufficiency and international trade need not be mutually exclusive. Considering frequent volatility in global food markets, overdependence on imports poses clear risks. To address food security challenges amidst production shortfalls, enhancing productive capacity is key. By understanding and improving self-sufficiency, policymakers can achieve a balance between increasing domestic food production and maintaining open international trade. This balanced approach ensures food security while leveraging the benefits of global trade.

5.3.2 Strengthening Domestic Agricultural Assistance and Promoting Technological Progress

Governments should increase support for agriculture to mitigate the negative impacts of trade liberalisation and climate change on domestic food production in the short term and to increase the positive effects of agricultural employment and arable land on food production. Because most countries view securing food supply capacity in times of crisis as a matter of national security and based on the risk of import disruptions due to conflict or political tensions, countries should invest in domestic agricultural capacity (Clapp, 2017). This can be done by actively promoting technological progress and innovation and increasing agrarian subsidies.

Agricultural science and technology are critical to improving food supply, and Governments can enhance food security by investing in agricultural science and technology. By strengthening research and development in agricultural science and technology, the cultivation of resilient crops can be encouraged to effectively cope with temperature fluctuations caused by climate change. Temperature fluctuations can pose a threat to food supply. Therefore, growing crops resilient to extreme climate change is crucial. This will help minimise the impact of unpredictable environmental changes on food production. At the same time, it is essential to encourage the adoption of farmers' insurance schemes to mitigate the financial losses suffered by farmers because of natural disasters or market fluctuations. This will also increase farmers' motivation to engage in agricultural production.

In addition, food supply can be secured by expanding the area of arable land and increasing the efficiency of food production per unit of arable land. Increasing the area of arable land will not only increase food production. Still, it will guarantee food security through research and development and improved crop yields, thereby increasing food production per unit of arable land.

Governments worldwide must prioritise food producers in their regions, as they are an essential food source and play a vital role in ensuring food security. Governments can provide direct financial subsidies to food producers and agricultural subsidies to small farmers and family farms. These subsidies can increase their capacity to produce food and make them more resilient. In addition, Governments can use these subsidies to strengthen agricultural infrastructure and increase the efficiency of agricultural production. Given the favourable impact of agricultural employment on food security, Governments can work with smallholder farmers by providing official guidance to improve their productive capacity and supplying them with seeds for planting. In addition, the Government could improve the mobility of skilled workers in the manufacturing sector, increase the agricultural labour force and provide farmers with ongoing training in cutting-edge agrarian technologies. This would enable them to acquire advanced agricultural skills, remain competitive, adapt to market fluctuations, and improve food security.

At the same time, many countries face financial resource constraints that limit the policies that countries can use - for example. In contrast, rich countries have the option of targeted agricultural investments; poor countries cannot implement such programmes and, therefore, use trade measures to promote food self-sufficiency. The gradual adoption of more open trade policies has increased food self-sufficiency and liberalised food trade more compatible.

5.4 Limitations of the Study

This research on food security has various constraints that could affect the strength and comprehensiveness of the results. A major drawback is the difficulty in acquiring complete and precise data on all factors that impact food security. More accurate results can be affected by the quality and detail of data related to factors like regional trade policies, localized climate variations, and the intricate impacts of climate change on food production systems. As a result, the limitations of these data may impact the strength and comprehensiveness of the study's findings, despite the valuable insights it offers.

The research uses fluctuations in per capita food production as a proxy measure for food security. While this method is dependable and commonly employed to assess food availability, it fails to encompass the complete intricacies of food safety. Food security is a complex idea that includes four main aspects: having enough food, being able to get food, using food wisely, and having a stable food supply. Although per capita food production can offer understanding of efficiency in production, it does not consider matters regarding fair distribution, availability, and the efficient utilization of food resources. Therefore, depending only on this measure may not provide a complete understanding of food security.

Furthermore, the study examines climate change, trade openness, and other potential factors influencing food supply stability, but it concentrates on a narrow range of variables. This method might not take into account other important factors of food security, like socio-economic conditions and policy effects. Thus, the results may not completely represent the intricacies of food security changes and could have restricted relevance for creating policies. For a more comprehensive grasp of food security, upcoming studies need to include a wider variety of indicators and factors that impact food security in practical settings.

5.5 Recommendations for Future Research

Given the complexity and diversity of the concept of food security, it would be advisable for future researchers to consider the different aspects of the idea and include as many factors related to food security as possible in their analyses. Variables such as unequal food distribution, quality and nutrition, dietary patterns, and availability over time contribute to the problem. Future research should provide an accurate picture of the food security situation and highlight the unique vulnerabilities of certain countries, regions or groups by employing a broader and more diverse set of indicators. Given the complexity of food security, relying on a wider range of factors can provide a more complete picture of the problem.

Conversely, the degree of food security varies widely across populations and regions. Therefore, stratified analyses are necessary when planning research to demonstrate the various manifestations of food security. By integrating multiple levels and categories of data, researchers can gain a deeper understanding of the complexity of food security. This increased understanding allows them to provide policymakers with more accurate and targeted recommendations for food security efforts.

The data for this study is limited to a specific period. Countries face different food security challenges due to differences in economic systems, geographical locations and regulatory frameworks. Therefore, given the magnitude of the challenges to global food security, the focus of future research must go beyond a single indicator to create a more comprehensive analytical framework along with more accurate policies. Given the complexity of food security issues, any study inevitably has limitations. However, future researchers can deepen our understanding of food security challenges by conducting diverse and comprehensive analyses. This will help lay a solid foundation for effectively addressing food insecurity.

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Appendices

Appendix 4.1: Descriptive Statistics

Date: 07/14/24 Time: 20:40
Sample: 1 2961

	FS	EMPLOY	GDP	LAND	POP	TEM	TRADE
Mean	20.71182	26.19746	13448.83	0.238682	1.372670	1.092920	85.21577
Median	13.80000	19.13784	5049.080	0.168555	1.246333	1.031000	76.21473
Maximum	190.9000	84.72688	112417.9	1.975975	19.36043	3.669000	442.6200
Minimum	0.400000	0.205770	322.4401	0.000267	-6.852118	-0.457000	15.68302
Std. Dev.	21.77181	22.39329	18232.40	0.249093	1.588742	0.548075	48.38236
Skewness	2.677743	0.707770	2.078199	2.869897	2.804309	0.654889	2.746067
Kurtosis	13.22582	2.365020	7.746943	14.63912	27.27788	3.738545	15.39723
Jarque-Bera	16439.54	296.9577	4911.449	20778.11	76600.09	278.9467	22683.08
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	61327.70	77570.69	39821991	706.7372	4064.476	3236.137	252323.9
Sum Sq. Dev.	1403075.	1484320.	9.84E+11	183.6603	7471.340	889.1435	6928923.
Observations	2961	2961	2961	2961	2961	2961	2961

Appendix 4.2: Panel Unit Root Test in Level with Intercept

Panel Unit Root Test on LNFOOD

Panel unit root test: Summary
Series: LNFOOD
Date: 07/14/24 Time: 22:05
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.39281	0.0000	151	2728
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.35930	0.0000	151	2728
ADF - Fisher Chi-square	528.063	0.0000	151	2728
PP - Fisher Chi-square	426.589	0.0000	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel Unit Root Test on LNTRADE

Panel unit root test: Summary
Series: LNTRADE
Date: 07/14/24 Time: 22:15
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.95795	0.0000	151	2756
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.18346	0.0145	151	2756
ADF - Fisher Chi-square	380.330	0.0015	151	2756
PP - Fisher Chi-square	368.723	0.0052	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNTEMP
Date: 08/23/24 Time: 02:26
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-20.8490	0.0000	151	2750
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-16.9722	0.0000	151	2750
ADF - Fisher Chi-square	904.607	0.0000	151	2750
PP - Fisher Chi-square	1218.73	0.0000	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNTRADETEMP
Date: 08/23/24 Time: 02:28
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-21.6685	0.0000	151	2749
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-17.2215	0.0000	151	2749
ADF - Fisher Chi-square	916.307	0.0000	151	2749
PP - Fisher Chi-square	1276.52	0.0000	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNLAND
Date: 08/23/24 Time: 02:30
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.94402	0.0000	151	2702
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-10.4501	0.0000	151	2702
ADF - Fisher Chi-square	550.106	0.0000	151	2702
PP - Fisher Chi-square	907.865	0.0000	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNPOP
Date: 08/23/24 Time: 02:33
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.11174	0.0000	151	2599
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.95478	0.0000	151	2599
ADF - Fisher Chi-square	927.395	0.0000	151	2599
PP - Fisher Chi-square	504.191	0.0000	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNGDP
Date: 08/23/24 Time: 02:35
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-13.0232	0.0000	151	2723
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.20445	0.0000	151	2723
ADF - Fisher Chi-square	461.896	0.0000	151	2723
PP - Fisher Chi-square	577.328	0.0000	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNEMPLOY
Date: 08/23/24 Time: 02:37
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.97788	0.0000	151	2700
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	4.55107	1.0000	151	2700
ADF - Fisher Chi-square	323.264	0.1914	151	2700
PP - Fisher Chi-square	394.812	0.0003	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.3: Panel Unit Root Test in Level with Intercept and Trend

Panel Unit Root Test on LNFOOD

Panel unit root test: Summary
Series: LNFOOD
Date: 07/14/24 Time: 22:08
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.52347	0.0000	151	2706
Breitung t-stat	-3.33543	0.0004	151	2555
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.78363	0.0000	151	2706
ADF - Fisher Chi-square	430.580	0.0000	151	2706
PP - Fisher Chi-square	333.591	0.1020	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel Unit Root Test on LNTRADE

Panel unit root test: Summary
Series: LNTRADE
Date: 07/14/24 Time: 22:16
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.95094	0.0000	151	2745
Breitung t-stat	6.71787	1.0000	151	2594
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.58943	0.0048	151	2745
ADF - Fisher Chi-square	415.358	0.0000	151	2745
PP - Fisher Chi-square	341.897	0.0566	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNTEMP
Date: 08/23/24 Time: 02:26
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-31.7815	0.0000	151	2739
Breitung t-stat	-18.1058	0.0000	151	2588
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-26.1235	0.0000	151	2739
ADF - Fisher Chi-square	1210.44	0.0000	151	2739
PP - Fisher Chi-square	1514.63	0.0000	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNTRADETEMP
Date: 08/23/24 Time: 02:28
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-31.6790	0.0000	151	2734
Breitung t-stat	-18.0551	0.0000	151	2583
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-26.2708	0.0000	151	2734
ADF - Fisher Chi-square	1217.37	0.0000	151	2734
PP - Fisher Chi-square	1509.26	0.0000	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNLAND
Date: 08/23/24 Time: 02:31
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.09046	0.0000	151	2700
Breitung t-stat	1.26891	0.8978	151	2549
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.61555	0.0531	151	2700
ADF - Fisher Chi-square	411.036	0.0000	151	2700
PP - Fisher Chi-square	322.367	0.2011	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNPOP
Date: 08/23/24 Time: 02:33
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-11.6904	0.0000	151	2626
Breitung t-stat	5.62869	1.0000	151	2475
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.02891	0.0000	151	2626
ADF - Fisher Chi-square	573.213	0.0000	151	2626
PP - Fisher Chi-square	306.135	0.4229	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNGDP
Date: 08/23/24 Time: 02:35
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.16239	0.4355	151	2715
Breitung t-stat	9.24160	1.0000	151	2564
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	3.85928	0.9999	151	2715
ADF - Fisher Chi-square	337.443	0.0784	151	2715
PP - Fisher Chi-square	221.489	0.9998	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: LNEMPLOY
Date: 08/23/24 Time: 02:37
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.19813	0.0000	151	2698
Breitung t-stat	8.02852	1.0000	151	2547
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.72531	0.2341	151	2698
ADF - Fisher Chi-square	397.087	0.0002	151	2698
PP - Fisher Chi-square	366.377	0.0066	151	2810

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.4: Panel Unit Root Test in First Difference with Intercept

Panel unit root test: Summary
Series: D(LNEMPLOY)
Date: 08/23/24 Time: 02:37
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-22.8280	0.0000	151	2603
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-25.3116	0.0000	151	2603
ADF - Fisher Chi-square	1244.13	0.0000	151	2603
PP - Fisher Chi-square	2195.95	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel Unit Root Test on D(LNFOOD)

Panel unit root test: Summary
Series: D(LNFOOD)
Date: 07/14/24 Time: 22:08
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-37.3637	0.0000	151	2606
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-33.6161	0.0000	151	2606
ADF - Fisher Chi-square	1562.28	0.0000	151	2606
PP - Fisher Chi-square	2020.89	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel Unit Root Test on D(LNTRADE)

Panel unit root test: Summary
Series: D(LNTRADE)
Date: 07/14/24 Time: 22:16
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-33.9796	0.0000	151	2607
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-30.1484	0.0000	151	2607
ADF - Fisher Chi-square	1624.13	0.0000	151	2607
PP - Fisher Chi-square	1774.97	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNTEMP)
Date: 08/23/24 Time: 02:27
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-53.1123	0.0000	151	2518
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-53.0317	0.0000	151	2518
ADF - Fisher Chi-square	2536.16	0.0000	151	2518
PP - Fisher Chi-square	13999.8	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNTRADETEMP)
Date: 08/23/24 Time: 02:29
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-51.7037	0.0000	151	2513
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-52.4918	0.0000	151	2513
ADF - Fisher Chi-square	2515.25	0.0000	151	2513
PP - Fisher Chi-square	14659.0	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNLAND)
Date: 08/23/24 Time: 02:31
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-13.8346	0.0000	151	2605
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-24.6458	0.0000	151	2605
ADF - Fisher Chi-square	1222.88	0.0000	151	2605
PP - Fisher Chi-square	1704.48	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNPOP)
Date: 08/23/24 Time: 02:33
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-23.2087	0.0000	151	2514
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-21.6464	0.0000	151	2514
ADF - Fisher Chi-square	1334.24	0.0000	151	2514
PP - Fisher Chi-square	1569.58	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNGDP)
Date: 08/23/24 Time: 02:35
Sample: 2001 2020
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.4990	0.0000	151	2623
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-13.1677	0.0000	151	2623
ADF - Fisher Chi-square	742.620	0.0000	151	2623
PP - Fisher Chi-square	725.584	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.5: Panel Unit Root Test in First Difference with Intercept and Trend

Panel Unit Root Test on D(LNFOOD)

Panel unit root test: Summary
Series: D(LNFOOD)
Date: 07/14/24 Time: 22:09
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-30.7886	0.0000	151	2583
Breitung t-stat	-18.4788	0.0000	151	2432
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-25.3717	0.0000	151	2583
ADF - Fisher Chi-square	1170.17	0.0000	151	2583
PP - Fisher Chi-square	1579.63	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel Unit Root Test on D(LNTRADE)

Panel unit root test: Summary
Series: D(LNTRADE)
Date: 07/14/24 Time: 22:16
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-32.1196	0.0000	151	2566
Breitung t-stat	-8.62792	0.0000	151	2415
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-25.1846	0.0000	151	2566
ADF - Fisher Chi-square	1132.85	0.0000	151	2566
PP - Fisher Chi-square	1557.01	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNTEMP)
Date: 08/23/24 Time: 02:27
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-40.7731	0.0000	151	2495
Breitung t-stat	-26.2132	0.0000	151	2344
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-40.5868	0.0000	151	2495
ADF - Fisher Chi-square	1837.31	0.0000	151	2495
PP - Fisher Chi-square	2996.82	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNLAND)
Date: 08/23/24 Time: 02:31
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-75.4244	0.0000	151	2580
Breitung t-stat	-2.16249	0.0153	151	2429
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-27.2781	0.0000	151	2580
ADF - Fisher Chi-square	1019.78	0.0000	151	2580
PP - Fisher Chi-square	1219.87	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNPOP)
Date: 08/23/24 Time: 02:34
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-22.6864	0.0000	151	2492
Breitung t-stat	0.36494	0.6424	151	2341
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-17.2806	0.0000	151	2492
ADF - Fisher Chi-square	826.680	0.0000	151	2492
PP - Fisher Chi-square	768.718	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNGDP)
Date: 08/23/24 Time: 02:36
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.87377	0.0000	151	2583
Breitung t-stat	10.2840	1.0000	151	2432
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.74857	0.0000	151	2583
ADF - Fisher Chi-square	623.312	0.0000	151	2583
PP - Fisher Chi-square	626.109	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNEMPLOY)
Date: 08/23/24 Time: 02:38
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-18.4691	0.0000	151	2560
Breitung t-stat	1.78532	0.9629	151	2409
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-17.8595	0.0000	151	2560
ADF - Fisher Chi-square	934.356	0.0000	151	2560
PP - Fisher Chi-square	1305.30	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(LNTRADETEMP)
Date: 08/23/24 Time: 02:29
Sample: 2001 2020
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-39.6898	0.0000	151	2492
Breitung t-stat	-26.9704	0.0000	151	2341
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-40.0684	0.0000	151	2492
ADF - Fisher Chi-square	1813.05	0.0000	151	2492
PP - Fisher Chi-square	3001.64	0.0000	151	2659

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.6: Correlation Analysis

	lnfood	lntrade	lntemp	lntrad~p	lnland	lngdp	lnemploy
lnfood	**1.0000**						
lntrade	**0.0514**	**1.0000**					
	0.0051						
lntemp	**0.1244**	**0.1084**	**1.0000**				
	0.0000	**0.0000**					
lntradetemp	**0.1321**	**0.2211**	**0.9886**	**1.0000**			
	0.0000	**0.0000**	**0.0000**				
lnland	**0.4558**	**-0.2659**	**0.0496**	**0.0171**	**1.0000**		
	0.0000	**0.0000**	**0.0070**	**0.3524**			
lngdp	**0.2076**	**0.2941**	**0.1699**	**0.2085**	**-0.2492**	**1.0000**	
	0.0000	**0.0000**	**0.0000**	**0.0000**	**0.0000**		
lnemploy	**-0.0954**	**-0.3492**	**-0.2063**	**-0.2516**	**0.3873**	**-0.8910**	**1.0000**
	0.0000	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	
lnpop	**-0.2639**	**-0.0975**	**-0.1023**	**-0.1155**	**-0.1951**	**-0.2410**	**0.1883**
	0.0000	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**

	lnpop
lnpop	**1.0000**

Appendix 4.7: Pooled Ordinary Least Squares

```
Linear regression                               Number of obs     =      2,961
                                                F(7, 150)         =      19.07
                                                Prob > F          =     0.0000
                                                R-squared         =     0.3352
                                                Root MSE          =      .3386

                                   (Std. err. adjusted for 151 clusters in id)
```

lnfs	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
lntem	-.5502503	.8671757	-0.63	0.527	-2.263707	1.163207
lntrade	.1442774	.1501802	0.96	0.338	-.1524645	.4410194
lntradetem	.3338473	.4451108	0.75	0.454	-.5456495	1.213344
lnpop	-.3861325	.2324775	-1.66	0.099	-.8454859	.073221
lnland	.4173004	.05109	8.17	0.000	.3163514	.5182493
lngdp	.2259152	.0945769	2.39	0.018	.0390402	.4127901
lnemploy	.0440806	.1048749	0.42	0.675	-.1631423	.2513035
_cons	.6509896	.6393729	1.02	0.310	-.6123507	1.91433

Appendix 4.8: Fixed Effect Model (FEM)

```
Fixed-effects (within) regression               Number of obs     =      2,961
Group variable: id                              Number of groups  =        151

R-squared:                                      Obs per group:
     Within  = 0.0202                                         min =          9
     Between = 0.3891                                         avg =       19.6
     Overall = 0.3024                                         max =         20

                                                F(7,150)          =       2.53
corr(u_i, Xb) = 0.0567                          Prob > F          =     0.0174

                                   (Std. err. adjusted for 151 clusters in id)
```

lnfs	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
lntem	-.2784952	.3493426	-0.80	0.427	-.9687632	.4117728
lntrade	-.0382271	.0985207	-0.39	0.699	-.2328947	.1564405
lntradetem	.152235	.1834613	0.83	0.408	-.2102672	.5147373
lnpop	.0618353	.0689146	0.90	0.371	-.0743334	.1980039
lnland	.3382076	.1531034	2.21	0.029	.0356897	.6407254
lngdp	.3246792	.1441472	2.25	0.026	.0398579	.6095005
lnemploy	.0869083	.122393	0.71	0.479	-.1549286	.3287451
_cons	.1095818	.5904906	0.19	0.853	-1.057172	1.276335
sigma_u	.28415057					
sigma_e	.20778236					
rho	.65158786	(fraction of variance due to u_i)				

Appendix 4.9: Random Effect Model (REM)

Random-effects GLS regression — Number of obs = 2,961
Group variable: id — Number of groups = 151

R-squared: — Obs per group:
Within = 0.0196 — min = 9
Between = 0.4102 — avg = 19.6
Overall = 0.3183 — max = 20

Wald chi2(7) = 57.87
corr(u_i, X) = 0 (assumed) — Prob > chi2 = 0.0000

(Std. err. adjusted for 151 clusters in id)

lnfs	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
lntem	-.2687661	.3523843	-0.76	0.446	-.9594266	.4218944
lntrade	.0024634	.0889378	0.03	0.978	-.1718516	.1767783
lntradetem	.153864	.1842224	0.84	0.404	-.2072053	.5149334
lnpop	.0271771	.0632541	0.43	0.667	-.0967987	.1511529
lnland	.3921897	.0620217	6.32	0.000	.2706294	.51375
lngdp	.2947831	.0904177	3.26	0.001	.1175676	.4719986
lnemploy	.0771114	.0962574	0.80	0.423	-.1115496	.2657725
_cons	.2331479	.4431911	0.53	0.599	-.6354906	1.101786
sigma_u	.27205801					
sigma_e	.20778236					
rho	.63159099	(fraction of variance due to u_i)				

Appendix 4.10: Poolability F-Test

Fixed-effects (within) regression — Number of obs = 2,961
Group variable: id — Number of groups = 151

R-squared: — Obs per group:
Within = 0.0202 — min = 9
Between = 0.3891 — avg = 19.6
Overall = 0.3024 — max = 20

F(7,2803) = 8.24
corr(u_i, Xb) = 0.0567 — Prob > F = 0.0000

lnfs	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
lntem	-.2784952	.2810748	-0.99	0.322	-.8296296	.2726392
lntrade	-.0382271	.061337	-0.62	0.533	-.1584973	.0820431
lntradetem	.152235	.1460176	1.04	0.297	-.1340779	.438548
lnpop	.0618353	.0746346	0.83	0.407	-.084509	.2081796
lnland	.3382076	.0631214	5.36	0.000	.2144385	.4619766
lngdp	.3246792	.0631757	5.14	0.000	.2008036	.4485548
lnemploy	.0869083	.0662411	1.31	0.190	-.0429779	.2167944
_cons	.1095818	.3104712	0.35	0.724	-.4991935	.7183571
sigma_u	.28415057					
sigma_e	.20778236					
rho	.65158786	(fraction of variance due to u_i)				

F test that all u_i=0: F(150, 2803) = 33.59 — Prob > F = 0.0000

Appendix 4.11: Bruesch Pagan Lagrangian Multiplier (BLPM) Test

```
Breusch and Pagan Lagrangian multiplier test for random effects

        lnfs[id,t] = Xb + u[id] + e[id,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                    lnfs |   .1720587       .4147996
                       e |   .0431735       .2077824
                       u |   .0740156        .272058

        Test: Var(u) = 0
                             chibar2(01) = 10360.36
                          Prob > chibar2 =   0.0000
```

Appendix 4.12: Hausman Test

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |      fe           re          Difference       Std. err.
-------------+----------------------------------------------------------------
       lntem |   -.2784952    -.2687661       -.0097291        .0326653
     lntrade |   -.0382271     .0024634       -.0406904        .0234842
  lntradetem |     .152235      .153864        -.001629        .0161297
       lnpop |    .0618353     .0271771        .0346582        .0176572
      lnland |    .3382076     .3921897       -.0539821        .0506775
       lngdp |    .3246792     .2947831        .0298962        .0420469
    lnemploy |    .0869083     .0771114        .0097968        .0375316
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =  11.83
Prob > chi2 = 0.1062
```

Appendix 4.13: Cross Sectional Dependency

```
Random-effects GLS regression                   Number of obs     =      2,961
Group variable: id                              Number of groups  =        151

R-squared:                                      Obs per group:
     Within  = 0.0196                                         min =          9
     Between = 0.4102                                         avg =       19.6
     Overall = 0.3183                                         max =         20

                                                Wald chi2(7)      =     161.76
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000

------------------------------------------------------------------------------
        lnfs | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
       lntem |  -.2687661   .2794013    -0.96   0.336    -.8163826    .2788504
     lntrade |   .0024634   .0567174     0.04   0.965    -.1087007    .1136274
  lntradetem |    .153864    .145244     1.06   0.289     -.130809    .4385371
       lnpop |   .0271771   .0725786     0.37   0.708    -.1150743    .1694285
      lnland |   .3921897   .0377174    10.40   0.000     .3182649    .4661145
       lngdp |   .2947831   .0472203     6.24   0.000     .2022331    .3873331
    lnemploy |   .0771114   .0546482     1.41   0.158    -.0299971      .18422
       _cons |   .2331479   .2621363     0.89   0.374    -.2806297    .7469255
-------------+----------------------------------------------------------------
     sigma_u |  .27205801
     sigma_e |  .20778236
         rho |  .63159099   (fraction of variance due to u_i)
------------------------------------------------------------------------------


Pesaran's test of cross sectional independence =     2.326, Pr = 0.0200
```

Appendix 4.14: Wooldridge Test for Autocorrelation

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      150) =    495.158
           Prob > F =      0.0000
```

Appendix 4.15: Breusch-Pagan/Cook-Weisberg Test for Heteroskedasticity

```
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: i.i.d. error terms
Variable: Fitted values of lnfs

H0: Constant variance

    chi2(1) =   9.39
Prob > chi2 = 0.0022
```

Appendix 4.16: Modified Wald Test for Groupwise Heteroskedasticity

```
Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (151)  =    4330.86
Prob>chi2 =       0.0000
```

Appendix 4.17: Regression with Driscoll-Kraay Standard Errors

```
Regression with Driscoll-Kraay standard errors   Number of obs     =      2961
Method: Pooled OLS                               Number of groups  =       151
Group variable (i): id                           F(  7,     19)    =   3444.42
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.3352
                                                 Root MSE          =    0.3386
```

lnfs	Coefficient	Drisc/Kraay std. err.	t	P>|t|	[95% conf.	interval]
lntem	-.5502503	.3241279	-1.70	0.106	-1.228658	.1281572
lntrade	.1442774	.0526322	2.74	0.013	.034117	.2544378
lntradetem	.3338473	.1792213	1.86	0.078	-.0412672	.7089618
lnpop	-.3861325	.1213405	-3.18	0.005	-.6401011	-.1321639
lnland	.4173004	.0122066	34.19	0.000	.3917518	.442849
lngdp	.2259152	.0237589	9.51	0.000	.1761872	.2756431
lnemploy	.0440806	.0322473	1.37	0.188	-.0234138	.111575
_cons	.6509896	.2289366	2.84	0.010	.1718197	1.13016